Three Essays on Development Economics: Household Welfare

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ABSTRACT

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This dissertation contains three essays on development economics, addressing trade liberalization and inequality in Brazil, a large-scale child health intervention in Indonesia, and conceptual and methodological aspects of measuring household economic well-being. The three consider different aspects of household welfare and its determinants. The first chapter examines the effect of a macroeconomic policy on household welfare; the second chapter studies the effect of a microeconomic intervention on a component of household welfare, that of children; the final chapter explores how we might conceive of and measure household welfare itself.

Using nationally representative, economy-wide data, the first chapter investigates the relative importance of trade-mandated effects on industry wage premiums, industry and economy-wide skill premiums, and employment flows in accounting for changes in the wage distribution in Brazil during the 1988-1995 trade liberalization. Unlike in other Latin American countries, trade liberalization appears to have made a significant contribution towards a reduction in wage inequality. These effects have *not* occurred through changes in industry-specific (wage or skill) premiums. Instead, they appear to

have been channeled through substantial employment flows across sectors and formality categories. Changes in the economy-wide skill premium are also important.

Indonesia's *posyandu* program is a very large child health and nutrition intervention with over 200,000 posts in 65,000 villages, introduced in the 1980s. The second chapter examines the short- and medium-term effects of the program. While the field efficacy of the individual components – immunization, vitamin A supplementation, oral rehydration salts, and growth monitoring and nutrition education – has been well established, there has been little evidence from micro-data of integrated programs being successfully implemented at scale. However, using household-level data and exploiting differences in timing and location of new *posyandu*, it appears that the program reduced under-five mortality by 36 deaths per 1,000 children, which is consistent with the reduction we would expect from the known clinical efficacy of its interventions, and represents 40 percent of the national decrease from 1980-2000. The chances of being underweight or stunted were reduced by 19 to 26 percent, with the effect concentrated in children two years and younger. There is also evidence that improved nutritional status led to large increases in test scores (0.24 to 0.37 standard deviations). A comparison of costs per child and cost-effectiveness with similar programs in other countries and other interventions indicates that the *posyandu* program is amongst the most cost-effective child health care interventions ever implemented. The chapter briefly examines why this large-scale program was successful in Indonesia when there is limited evidence that similar programs have been effective elsewhere in the developing world.

The final chapter examines the construction and use of household indices with asset data, a recent and popular approach to measuring economic well-being. After outlining the conceptual relationships and differences between components of economic well-being and monetary measures, a rich Indonesian dataset is used to evaluate methods of index construction, including different combinations of the underlying asset indicators and the various approaches to weighting such variables (PCA, PFA, MCA and DiHOPIT). Different weights are shown to have generally little empirical difference. However, the choice of underlying variables is found to be important; most choices lead to a good measure of consumption, but only a few produce a good measure of wealth. Based on the empirical results and theoretical discussion, approaches are recommended for constructing asset indices given different research objectives. In addition, the potential bias when using or omitting asset indices as proxies for particular omitted variables is estimated. Multidimensional extensions measuring components of economic well-being separately are also introduced.

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ACKNOWLEDGEMENTS

Salad Days in New York: 6 Parts Gin, 1 Part Vermouth, with a Twist

This completed dissertation represents the conclusion of an episode begun ten years ago. Writing these acknowledgements, now in Indonesia, and glancing back over that decade, I realize quite how many people have contributed to it in such different ways. Through a brief accounting of these years, I hope to offer appropriate acknowledgement to all who have been a part of this work.

I had never intended to pursue PhD research; I knew few people who had entered graduate studies at any level, outside of the ubiquitous MBAs that were *de rigueur* within the management consulting fraternity. After three years of what was to prove invaluable experience, working for many firms in numerous industries on various issues across multiple continents, it came to be my time to apply to top US MBA programs, sponsored by (or indentured to, depending on your perspective) the firm, in order that I return newly minted, to be charged out at double the daily rate, albeit in a role similar to the one performed before I left. Being always the contrarian, I decided instead to spend some time alone writing and studying the mathematics required for the alternative studies I had chosen. For the space to do this, for the financial and personal support in studying a degree referred to by another partner in the firm as macramé, I will always be thankful to the managing partner, the late Chris Recny.

The Masters of Economics of Development program at the National Centre for Development Studies (now the Crawford School) at the Australian National University in Canberra was the beginning of my study and work in economics and development, as well as my introduction to Southeast Asia and Indonesia, a region I was to first research on and later practice in. Six months into my study, I realized that the development work I was interested in required a PhD in economics from a top international school, and so began the rather arduous application process to do so. The programs I was accepted into reflect the much appreciated recommendations I received from my ANU professors, Steve Dowrick, Patrick de Fontenay, Tom Kompas, and especially, Hal Hill.

The Economics Department at Columbia University was a relatively easy choice to make, being one of the top economics programs in the world, and located in the city I was to discover will always be home. However, my scholarship for full tuition and living costs was only to be for my second year and onwards; I would have to fund the first year myself. This made me hesitate, concerned that the consequent debt would restrict my opportunities upon graduating to those with a commensurate remuneration. My youngest brother Clayton, as he so often is, was the more perceptive, and thanks to him, my PhD "will always be from Columbia University". This decision was made ever more easily for the financial support offered by Clayton, my dad, Paul, my uncle, Ray, and Jacquie Leong. For making the first and subsequent years possible, I thank all of them.

I have always felt lucky in life, giving so much of myself to it, and having so much returned. Life is best lived in episodes, and every episode has always seemed vital to me. However, I suspect I will always consider my (initial) time in New York as the most productive and playful, intense and varied, important and life-defining of all, as much as I thrill in what I do now and eagerly anticipate the new directions to come. The many and varied people who made New York so wonderfully right for me, I thank now.

The first year of an economics doctoral program is an experience difficult to understand for those who have not undertaken it, condescending as that might sound (a tone that most of those mentioned here will not find wholly unfamiliar). While having been 'enriched by it, transformed by it, made by it, lived through it' are possible descriptions, 'suffered and persevered through it' is perhaps most apt. Many of my cohort who also went through the year I consider the hardest of my life thus far would go on be an important part of my New York experience: Raj Advani, Dan Carvell, Shubha Chakravarty, Tumer Kapan, Ayako Kondo, Enrico Manlapig, Justin Svec, Megan Torau, Simeon Tsonev. Students from other years would also contribute to my time at Columbia, including Camilia Minoiu, Gideon du Rand and Guru Sepathy.

For the first two years in New York I lived in a Columbia graduate student apartment in Morningside Heights, the northwestern Manhattan neighborhood where the school is located. By 30 years old you gain sufficient experience from shared living to know that you either live with good friends, your partner, or alone; unknown flat mates, randomly assigned or with a minimal mediation through a process of advertisement, are, at best, an exercise in tolerance and acceptance. I thus had the great gift of living with two of the smartest and genuine people I have had the pleasure of knowing, Mike Brent and Andrew Hall. Ticking the vegetarian box on one of Columbia's many, many forms led to endless evenings of philosophical discussion, pub discussion, triumphs and defeats on the pool table, and a rewarding relationship with Simon, a teleporting cat who taught me that cats can be quite happy apartment dwellers, and would thus later make possible Herbert Stencil. Steamy New York Augusts will always mean cooking house meals, a glass of wine in hand with Mike cleaning up in my wake. Along, of course, with evenings spent at the 1020 dissecting matters great and small, or taking in the latest Mets' semblance of baseball at Shea, of which more later.

I later moved out to Brooklyn, which was to remain home for the next four or so years. And home it was, with Sandy, Scat, Gladys, and their entire clan living downstairs, Shane Minken upstairs, and Andrea Miller, Sarah Thomas and Rob Link, and the Crazy Russians (Mila and Numar) down the road. Freddy's, Franny's, the Black Sheep, Alchemy, Farm, Beast. Running around Prospect Park with Raj. The Mendoza Line at Southpaw. Brooklyn will always be the place I return to.

When I began at Columbia, my intention had been to study the theoretical macroeconomics of development, especially the relationship between growth and inequality. However, development economics had in a sense moved elsewhere; many

of the key issues of interest are micro and empirical, where the link between policy and academia is tighter and less research had focused. The young professors who were to teach, guide and mentor me from second year on are all working at the frontier of development research, addressing issues of individuals, households and firms, and ranging from the effects of health and education policies, to trade, employment and inequality. The core of development economics is no longer a single paper expounding a grand theory of development, but a body of knowledge about what works and what does not, built up from a substantial body of work which carefully examines how a single policy or effect plays out in a specific location and context, repeated a number of times to understand what is common across all contexts and what is specific to the setting. This careful empirical approach is methodically establishing evidence of how poor countries can better develop, and how the poor in poor countries can move out of their situation. In particular I thank Doug Almond, Miguel Urquiola and Eric Verhoogen. Most of all, I think Kiki Pop-Eleches, my advisor and friend, who oversaw my research at Columbia, who knew when to give me space to explore, when to rein me in, and always guided my work along the right path. I am also appreciative of the other members of my defense committee for their time and comments, Leigh Linden and Dan O'Flaherty, as well as Sy Spilerman and Florencia Torche.

Sy and Florencia are sociologists rather than economists, and one of the critical strengths of my education at Columbia was the multidisciplinary nature of it. I met Sy first when I took his class on inequality, in which I retain a keen interest. As Kiki once

mentioned, sociologists are most certainly asking the right questions, and I was interested in understanding how they thought about the nature and determinants of inequality, a subject of insufficient focus in economics. From my class paper on estimating household economic status from proxy indicators, Sy, Florencia (now at New York University) and I began exploring further what these increasingly commonly used measures really mean, and attempted to make clearer the distinctions between the related concepts involved and to identify which methods are most appropriate. While this collaboration continues, the initial results are the basis of Chapter Three. Working with Sy and Florencia has greatly enhanced my ability to conceive and write papers, as well as exposing me to uncommon approaches to common problems.

Multiple approaches to common problems summarizes my time at Columbia. There exists a sole reason for my multidisciplinary training and framework in development: Joe Stiglitz's Globalization and International Development program, funded by the National Science Foundation's Integrative Graduate Education and Research Traineeship (IGERT), of which I had the great privilege of being an inaugural member. Joe used seed money from the NSF to establish a program at Columbia that would draw together professors and graduate students from a range of social sciences, including political science, sociology, law, public health and communications, as well as economics. This program had a number of requirements, all additional to those of our departmental programs. We studied at least two graduate courses from other departments, and a range of multidisciplinary courses established especially for the program. Most importantly, we

met every week to present and discuss our own work, to subject it to critiques and perspectives from disciplines beyond our own. It is not at all inaccurate to say that this weekly meeting was the central focus of my university life while at Columbia. I learnt more from my colleagues and friends in IGERT than any from other source. They are all incredibly talented, passionate and committed people who represent the best of us, and will forever remain at the heart of my Columbia experience. They include Gabriella Carolini, Ernesto Castadena, Dan Choate, Ashley Fox, Guy Grossman, Marissa King, Emily Lundberg, Dan Neilsen, Ngoni Munemo, Laura Paler, Cuz Potter, John Powers and Matt Winters.

IGERT was established by Joe Stiglitz, but run every day under the guidance of Akbar Noman, notably with assistance from Eva Kaplan. Akbar epitomizes the culture of IGERT: smart, passionate and committed, as I have said, but also debonair, erudite, urbane, and with a great love of the social. To borrow a term from Gabriella, it was in fact Akbar who was, ultimately, our fearless leader, and he to whom we all turned.

It was through IGERT and its sister organization, the Initiative for Policy Dialogue (IPD), also established by Joe, that I was eventually to find myself in Indonesia. I was already using Indonesian data in my research, particularly in my work with Sy and Florencia, and had an interest in both Southeast Asia and Indonesia since my tutelage under Hal at ANU. Joe was interested in establishing a relationship with the Brighten Institute, an Indonesian political and economic think tank. IPD provided funding for me to visit

Indonesia for four months, where I was to conduct my primary and secondary research on the long term effects of Indonesia's village health posts (*posyandu*), which forms Chapter Two of this dissertation. This was conducted while based at the Brighten Institute and as a visiting scholar to the University of Indonesia and the Bogor Agricultural University, and for both financing and facilitating this, I owe Joe a great deal, as well as to Eva, who worked hard behind the scenes to set it up.

My research in Indonesia was greatly facilitated by the Brighten Institute, and thanks are due to all involved there, in particular Dicky Firmansyah, Hermanto Siregar and Sonny Priyarsono, without whose assistance I would have been unable to make the necessary contacts to further my research, and in particular Dwi Wahyuniarti, who became my *de facto* research assistant, making appointment and introductions, accompanying me to meeting and taking notes, tracking down data, and generally assisting in a manner well beyond that required. Many interviews were conducted in Jakarta and there are far too many individuals to mention, but thanks must be made given to Vivi Alatas, Atmarita, Aswatini, Fajar, Stephanus Indradjaya, Jarot, Maliki, Minarto, Rachmat, Claudia Rokx, Professor Soekirman, Sugiri, Dr Haryono Suyono, Thee Kian Wee, Trihono, and Bill Wallace. These and many other people made time to talk to me about the *posyandu*, their history, design, data sources, and suggested yet other people to meet. Hal Hill introduced me to a number of these contacts, for which I thank him again. Critical data were made available to me by Kathleen Beegle and John Strauss, without which I could not have completed key analysis, and I am forever grateful for this.

However, the most important support for my Indonesian research was without a doubt provided by Irfan Nasution, who was with the Brighten Institute. Irfan worked tirelessly to facilitate every part of my research, from introducing me to academics, university administrators, and government officials, to assisting me through the accreditation process necessary to conduct research in Indonesia, to showing me where to get a good beer in Bogor. I spent much time in Jakarta, Bogor and Depok with Irfan, and his wonderful family, Leny, Ais, Basel and Ernesto. Irfan was much more than a colleague in Indonesian development, he was a very dear friend and is much missed by all who knew him. This dissertation, and especially Chapter Two, is dedicated to his memory.

Before my time in Indonesia, a notable component of my education was a summer spent in DC with Chico Ferreira in the Development Research Group of the World Bank. During this time, I worked with Chico and Philippe Leite to develop a paper examining the effects of trade liberalization on the household income distribution in Brazil, which was to greatly expand my analytical toolkit, and was the basis for Chapter One. I thank Chico for this opportunity; for setting this up, and facilitating what was to be my initial experience at the Bank, where I now enjoy such fulfilling work, I thank Miguel Urquiola.

I would like to close these acknowledgements by taking some time to mention the many friends I have been blessed with who supported me during my time at Columbia, before and beyond. Some I have known for many years, some I met first in New York, but they have all shared a part of this experience.

First, my closest friends from IGERT, Cuz Potter, Gabriella Carolini, Dan Choate, Marissa King, Dan Neilsen, Laura Paler, Matt Winters, and Brad Winer (honorary). With others, they formed the core of the stalwart crew of the 1020 – our watering hole of choice, a home away from home, and a perfect capsule of everything that is inspiring about graduate school, being one part development shop talk, one part political debate, one part storytelling, one part Brooklyn Lager, and four parts dark and cool. If not at the 1020, you might otherwise find us at the late and surprisingly lamented Shea Stadium, home to young Gabriella's and my beloved Mets, who would usually find a way to make the long ride home on the 7 train even longer, but we never minded, for that is why we love them. Other good friends from New York, with whom much time at various points was spent exploring the great cultural offerings of New York, particularly Angel's Share and subsequently B-flat, included Aarthi Belani, Anne Hubert, Anne Keller, Ashish Lal, Ashley Lester, Jay Majumdar, and James Vickery. This dissertation would have been completed without them, and probably a year or two earlier, but my New York would never have been the same.

Nor would New York have been complete without Neal Wallace and Emma Bredin, two of the first people I met after arriving. Their time in New York (and their relationship, and later marriage and mortgage), coincided my own. From early days exploring downtown New York (and occasionally bathroom duties in Hobvegas), to karaoke with Goliath at the Racoon Lounge, to Christmas Eves at Boots and Saddles, to Porkfests and

Christmas dinners at their apartment, they have been good support and the greatest of friends.

My family and oldest friends have been a constant. All of them, at various times, have visited, sent care packages and love, provided respite at their homes when I needed a break most and cajoled me into finishing when I was motivated least. They include Jason Biggs, Penny Brown, Giovanni Donaldson, Marenco Kemp and Erica Wald, Daniel Maurer, and my family Dad and Vic, Clayton and Megan, Trent and Marie (and now Finn, although he has yet to see a Mets game), and Ray and Jan. That which is concupiscible in my life cannot be told without all of them, but, sadly, here is not the place.

Finally, this dissertation would not have been possible without two people.

I first met Bruce Preston in September 2003, when he taught one quarter of our macroeconomics sequence. It was Bruce's first year at Columbia also, although as an assistant professor rather than enjoying my lowly graduate student status. We exchanged friendly comments a few times after class, and agreed to get a drink when the semester was over. That drink was had at the 1020, naturally, where we met at 4pm for a couple of beers. As it turned out, those couple of beers stretched out over twelve hours and an entire New York snow storm. We sat down in the fading but clear afternoon light, watched the first flakes fall, then the uncountable others, while we ranged over economics, sport, antipodean politics, music, literature, beer, gin, vodka, pool, and surely others. Upon being thrown out at 4am (even the 1020 must close eventually), we wandered happily, if a little unevenly, up a pristinely white and chaste Amsterdam Avenue; I didn't tell him about the bats; he would see them soon enough. Over the next six years, Bruce was always there, or thereabouts, both a source and palliative to the almost daily katzenjammer. Our New York adventures were many and varied (and surely far from an end), but it was with Bruce (and Rebekah) whom I spent much of my time (and most of my stipend) at the Mercury Lounge, Bowery Ballroom, Angel's Share and B-Flat, 1020, and Sing-Sing, not to mention numerous evenings reminiscing about Scott Baio and his much celebrated television career. As my professor, he always had the right advice for navigating the hazardous channels of graduate studies in economics; as my attorney, he always had the right advice for running eagerly onto the shoals of New York's hazardous distractions; as my banker, he sponsored some of my more extravagant evenings; he is and will always be more than a best friend.

I met Rebekah Pinto perhaps two months after my first drinks with Bruce. We both tell different stories about our initial meeting, and the disparities suggest perhaps how shrouded in myth the origins of our relationship are. Even more than Bruce, Rebekah is that without whom my time in New York is unimaginable, for it would have been a world utterly changed. Rebekah was there through the tempest of first year, and the calmer waters that were to follow; the absences in DC and then Indonesia; the long nights poring over code and the long mornings with Dawson and friends. What needs to be expressed to her would form an entirely fourth chapter, and unsatisfactory as it is to relegate such efforts to later times, thus it must be. It was with Rebekah that I moved to Brooklyn, and with me that she moved to Indonesia. It was with her family (Linda and Ralph, Sarah and now Juanjo, Gretchen and now Mike) that I spent many a summer sweat, many a winter chill, many a snow day in Brooklyn, many a weekend in the fine state of New Jersey, and at whose family estate in Pennsylvania that I finally completed this tome which lies in front of the good reader, should they have made it thus far through these meandering reflections, self-indulgences, and genuine gratitudes. Rebekah, you are a Mendoza Line in Brooklyn: all that I seek.

With less than the smallest epsilon of doubt, there are those whom I have omitted. Please accept my thanks and apologies, but know that you were a part of this, a record of my time and work, my salad days, in New York.

DEDICATION

This dissertation is dedicated to the memory of Irfan Nasution and Margaret Anne Soper.

Chapter One: Trade Liberalization, Employment Flows and Wage Inequality in Brazil[1]

1.1 Introduction

The hypothetical link between 'globalization' and inequality (within developed countries, within developing countries, or between them) has been the subject of a vast literature over the last twenty years. Even a cursory review of this literature reveals that 'globalization' has been a "catch-all term that is used to describe phenomena as diverse as trade liberalization, outsourcing, increased immigration flows, removal of capital controls, cultural globalization and generally faster transmission of international shocks and trends" (Goldberg and Pavcnik 2004: 1). In this chapter, we will focus on evidence pertaining directly to trade liberalization although, in some cases, it is difficult to separate the impacts of trade liberalization strictly defined from those of outsourcing, or of increased flows of technical and managerial knowledge.

Most of the literature on trade liberalization in Latin America has focused on Mexico, Chile and Colombia, and suggests that it has contributed to an *increase* in inequality (or at least in the gap between skilled and unskilled wages). Since there was a presumption that Latin America, like most other developing regions, was abundant in unskilled labor,

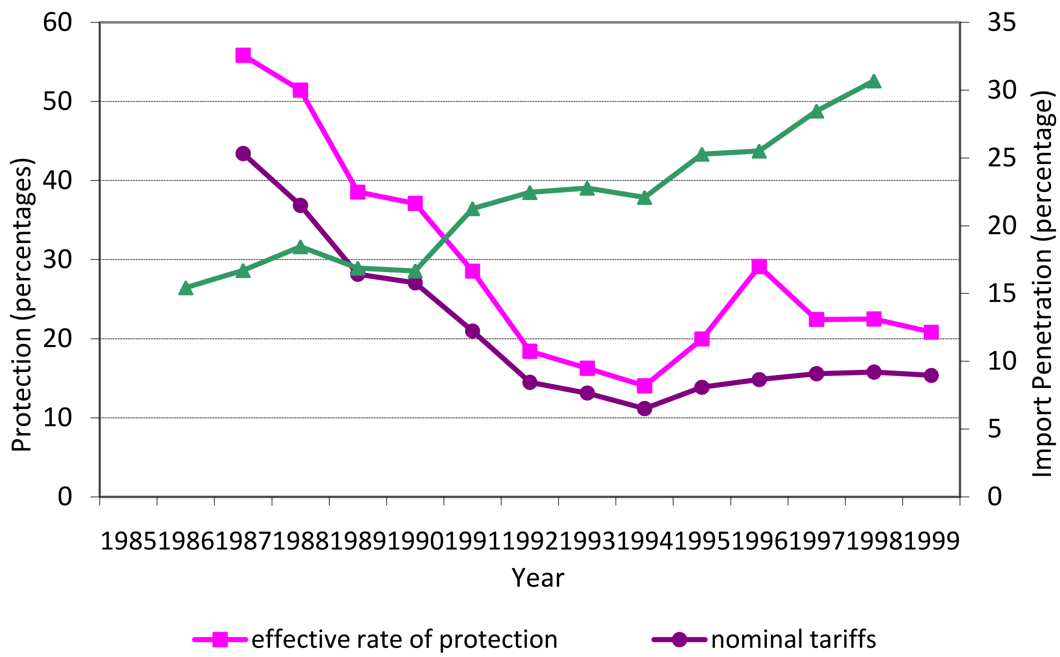
[1] With Francisco H.G. Ferreira and Phillippe G. Leite of the World Bank's Research Department. We are grateful to Nina Pavcnik and Norbert Schady for kindly sharing their constructed industry concordance with us; and to Gustavo Gonzaga, Will Martin, Nina Pavcnik, Guido Porto and Erik Thorbecke for helpful conversations or comments. All errors and omissions are exclusively our responsibility. The views expressed in this paper are solely those of the authors, and they should not be attributed to the World Bank, or any other organization.

this empirical finding appeared to contradict the predictions of the ('two countries, two goods, two factors' version of the) Stolper-Samuelson theorem in Hecksher-Ohlin trade theory. Although the next section briefly reviews some of this literature, this chapter focuses on Brazil, a country where trade liberalization appears to have been *inequality-reducing*.

Previously one of the most heavily protected economies in the world, Brazil experienced an episode of marked trade liberalization between 1988 and 1995. Average nominal tariffs (weighted by lagged industry imports) fell from 43.4 percent in 1987 to 13.9 percent in 1995. Effective rates of protection fell from 55.8 percent to 20.0 percent in the same period. These large changes in protection had a correspondingly large impact on trade flows: import/consumption ratios across all manufacturing sectors rose from 15 percent in 1986 to 31 percent in 1998. Figure 1.1 shows the evolution of both tariff rates and trade flows over the 1985-1999 period.[2] It has also been argued that this episode of trade liberalization had a substantial impact on labor and total factor productivity growth, with the latter increasing by six percentage points in annual rate terms (Ferreira and Rossi 2003).

[2] The data reported in Table 1.1 weigh tariff rates by lagged industry imports. An alternative weighting scheme (by industry value-added) generates an even more pronounced decline: citing data from Kume *et al.* (2000), Abreu (2004) reports a decline in nominal tariffs from 54.9 percent in 1987 to 10.8 percent in 1995. Effective rates of protection fell from 67.8 percent to 10.4 percent in the same period.

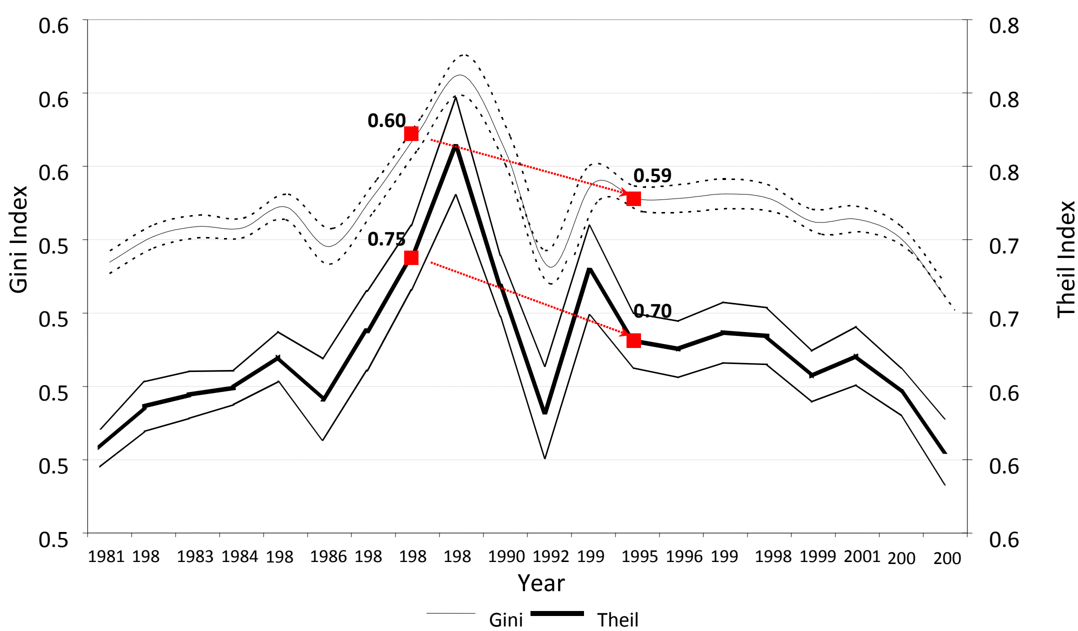
Fig. 1.1. Protection and import penetration in Brazil, 1985-99.



Source: Tariffs and rates of protection from Kume *et al.*(2000) in de Paiva Abreu (2004); import penetration from Muendler (2003).

During this period Brazilian inequality, which had been rising until 1989, started a gradual but persistent decline. Figure 1.2 shows the long-term evolution of two commonly-used inequality measures, the Gini and the Theil indices, between 1981-2004, for household income per capita. The bands around the point estimates denote the 95 percent bootstrapped confidence intervals. The figure highlights the trade liberalization period of 1988-1995, during which inequality briefly rose (for one year) and then began to fall. The Theil index fell from 0.75 to 0.71 and the Gini fell by almost two points from 0.61 to 0.59 over this seven-year interval. Both declines are statistically significant at the 1 percent level. As shown in Figure 1.3, inequality also fell in the distribution of hourly wages: the Gini fell by almost three points, from 0.61 to 0.58 and the Theil fell from 0.78 to 0.72. Both declines are significant at the 5 percent level. The economy-wide skill-premium (defined as the ratio of the wages of skilled workers to those of unskilled workers) fell by 14.3 percent (see Figure 1.4).[3] Looking only at the skill premium in manufacturing, Gonzaga *et al.* (2006) find a similar (15.5 percent) decline between 1988 and 1995.

Fig. 1.2. Household per capita income inequality in Brazil, 1981-2004



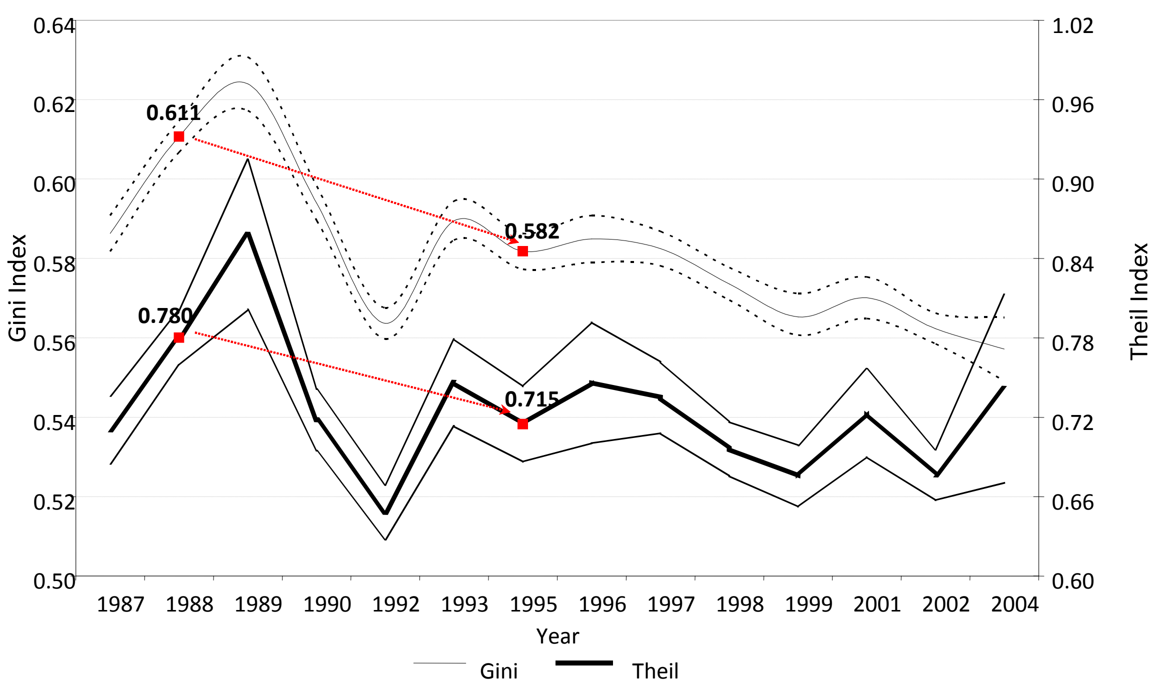
Source: Ferreira, Leite and Litchfield (2008).

Were these two phenomena linked? Did trade liberalization (and other aspects of increased openness which took place alongside it) cause at least part of the contemporaneous decline in Brazilian inequality? The literature is somewhat

[3] We use an education-based definition of skill: skilled workers have 11 or more years of schooling; and unskilled workers are those with ten or fewer. We return to a discussion of this definition and alternatives below.

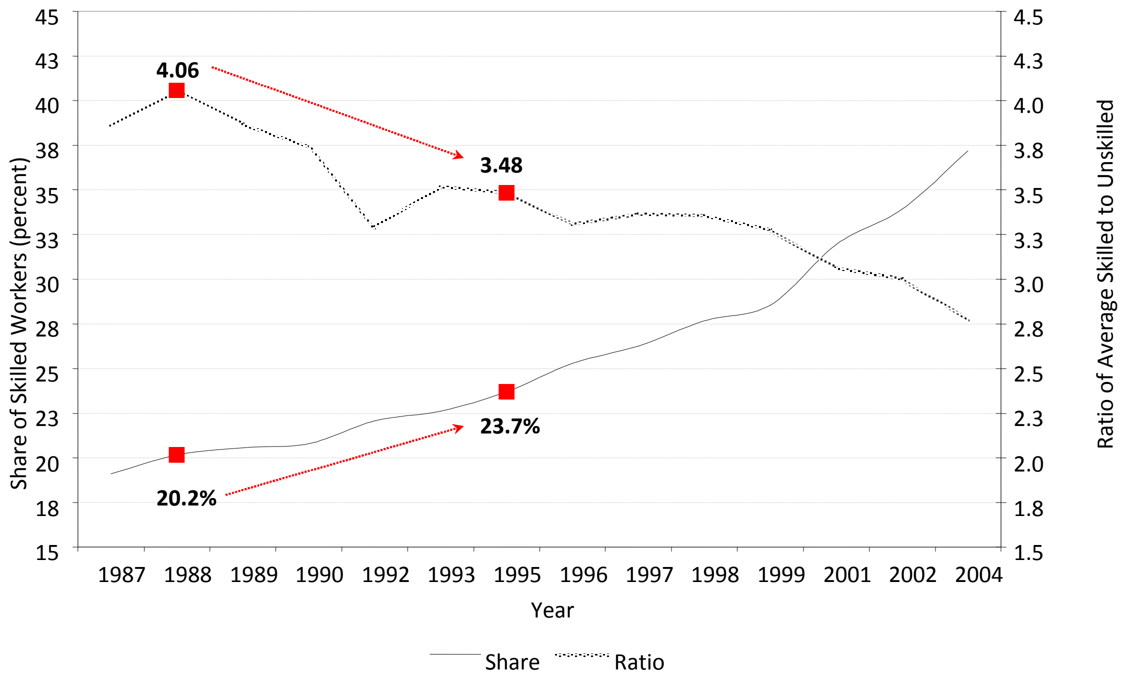
inconclusive. Focusing on the specific channels of industry wage premiums (and industry-specific skill premiums) Pavcnik *et al.* (2004) find no evidence of any effect from trade liberalization on the Brazilian wage distribution. More recently, Gonzaga *et al.* (2006) argue persuasively that, through the more general channel of changes in the economy-wide skill premium (as opposed to industry-specific premiums), trade liberalization did reduce wage disparities in Brazil. Although these two studies cover the same period, they use different data sets and methodologies, which lead them to focus on different aspects of the same phenomenon.

Fig. 1.3. Hourly wage inequality in Brazil, 1987-2004



Source: Authors' calculations from PNADs.

Fig. 1.4. Skill wage premium and share of skilled workers in total employment, 1987-2004



Notes: Unskilled workers have ten or fewer years of schooling; skilled workers have eleven or more years of schooling.
Source: Authors' calculations from PNADs.

Despite their differences, both studies focus on workers in manufacturing only. The manufacturing sector accounted for 16 percent (13 percent) of total employment in 1988 (1995) and there can be no *a priori* presumption that changes in the skill premium in that sector drive national wage inequality. During this same period, there has also been a convergence between urban and rural incomes in Brazil, which is often attributed to agricultural growth.[4] Although agriculture is eminently tradable, it has not to our knowledge been included in any analysis of liberalization and distribution in Brazil.

[4] See Ferreira, Leite and Litchfield (2008).

This paper seeks to revisit the evidence on Brazil's trade liberalization in a more comprehensive way. We innovate in four ways. First, we combine the approach used by Pavcnik *et al.* (2004) to study trade-mandated changes in industry-specific wage and skill premiums, with a consideration of the economy-wide skill premium on which Gonzaga *et al.* (2006) focus, and ask what was the combined effect of the two channels on the wage distribution in Brazil. Second, unlike previous studies, our analysis covers workers in all sectors of the economy, including agriculture and services. Third, we explicitly consider employment responses to the tariff and exchange rate changes that took place over the period, investigating a channel of impact which is generally acknowledged as potentially important in theory, but seldom studied in practice. Fourth, we use our estimated models of wages and employment levels to simulate counterfactual wage distributions which allow us to decompose the changes in distribution actually observed over the seven years of trade liberalization into various components – some directly attributable to trade reforms, some which may or may not reflect trade changes, and some which are most likely independent of trade factors.

Our main findings are, first, that trade liberalization in Brazil did in fact contribute to the observed reduction in wage inequality in the entire Brazilian economy – and not just in manufacturing. As argued by Gonzaga *et al.* (2006) – and unlike in Chile, Mexico and Colombia – Brazil's pre-liberalization tariffs (adjusted by import penetration) were highest for skill-intensive goods. These tariffs fell by more than those for other goods, leading to a decline in their relative prices. Consistent with the simple Stolper-

Samuelson theorem, this decline led to a decline in skilled wages, relative to those of unskilled workers, and to a movement of workers away from previously protected industries. As Pavcnik *et al.* (2004) found, other channels of impact through industry-specific wage and skill premiums were unimportant.

Second, the decomposition results suggest that:

i. Changes in industry-specific wage premiums and skill premiums were unimportant. Although changes in tariffs have the expected sign, the overall effect on the wage distribution was negligible.

ii. The bulk of the trade impact on the wage distribution occurs through the employment and occupational reallocation that took place in response to changes in tariffs and relative prices. This effect accounts for a substantial fraction of the observed reduction in inequality between 1988 and 1995.

iii. Changes in the economy-wide returns to skill – which may be at least partly driven by trade reforms – contributed to a further reduction in inequality (as did changes in other returns).

iv. Changes in the joint distribution of (observed and unobserved) worker characteristics were inequality-increasing, and partly offset some of the trade-driven changes in inequality.

The chapter is organized as follows. The next section provides a very brief overview of the literature, focusing on the conceptual channels through which trade reforms affect the distribution of incomes, and on five or six specific theoretical mechanisms through which openness has been hypothesized to affect wages and employment. Section 1.3 describes our data sets and the methodological approach. Section 1.4 presents the estimation results for a set of wage and employment regressions. Section 1.5 discusses a decomposition of the changes in Brazil's wage distribution between 1988 and 1995, drawing on counterfactual distributions constructed on the basis of the models estimated in Section 1.4. It also discusses the implications of the wage decomposition for poverty and inequality more broadly, measured in the distribution of household per capita incomes. Section 1.6 concludes.

1.2 A Brief Literature Review

The literature on the relationship between 'globalization' and distribution is now so extensive that Goldberg and Pavcnik (2004) open their recent survey of the subject by noting that "the number of literature reviews alone is so large by now, that it seems that a review of literature reviews would be appropriate" (p.1). Given the existence of two excellent recent surveys – Winters, McCulloch and McKay (2004) and Goldberg and Pavcnik (2004) – we make no attempt at an exhaustive review here. Instead, this section briefly reviews two sub-themes which are of particular importance for our analysis in this chapter: the channels through which trade reforms affect the distribution of income (and hence inequality and poverty); and the recent evidence on the distributional effects of trade reform in Latin America in general, and in Brazil in particular.[5]

1.2.1. Channels of Impact from Trade Liberalization to Household Incomes

If openness to the international economy brings persistent gains in terms of access to new knowledge and technology, or sustained gains in the growth rate of total factor productivity, then it is possible that trade liberalization leads to faster long-run economic growth. Whether or not this is in fact the case has been the subject of a debate, with Sachs and Warner (1995) and Edwards (1998) among the proponents, and Rodriguez and Rodrik (2001) leading the skeptics. The current balance of opinion seems to be that "despite the econometric and conceptual difficulties of establishing beyond doubt that openness enhances income levels, the weight of experience and evidence seems strongly in that direction" (Winters *et al.* 2004: 78).

If this is indeed the case, the effect of trade on growth, whether it is mediated through a faster rate of technology adoption or through greater dynamic efficiency gains from competitive pressures, is likely to be of first order importance in any understanding of the relationship between 'globalization' and poverty, and policy makers should bear it very much in mind. Nevertheless, this chapter belongs to the (large) strand of literature that seeks to understand the static or short-term impacts of trade liberalization on the distribution of incomes. When tariffs (or non-tariff barriers) are reduced or eliminated,

[5] See also Nissanke and Thorbecke (2006) for a thoughtful discussion of the links between globalization and distribution.

the domestic prices of the relevant goods change. These price changes can affect household incomes (or consumption) through five main direct channels, namely:

Output and input prices. If household members are self-employed, producing, trading and consuming different goods, then the first-order approximation to the change in their welfare as a result of changes in the price vector is simply $\Delta W = \sum_i (q_i - c_i)\Delta p_i$.[6] The basic insight is that net producers of those goods whose prices fall as a result of trade reforms lose out, while net consumers gain.

Wages. For household members who are employed, the first effect of price changes is through the knock-on effect on factor prices, and crucially on the individual's wage. The exact transmission mechanisms depend on the degree of competition in both factor and product markets, but the benchmark result under competitive markets is that as protection declines and relative goods prices move against the previously protected good, relative factor prices also move against the factor in which the protected good is intensive. This is the well-known Stolper-Samuelson theorem in Hecksher-Ohlin trade theory.[7]

Employment. In response to changes in profitability that arise because of the aforementioned changes in product and factor prices, the composition of production

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[6] See Deaton (1997), and discussion in Winters *et al.* (2004).

[7] The theorem generates less clear-cut results in a world with more than two countries, goods or factors of production but, as we shall see, the basic insight from the 2x2x2 version of the theorem remains remarkably powerful.

typically changes after trade reforms. Industries whose product prices have fallen contract, and those whose relative product prices have risen expand. In response, there is a reallocation of employment across sectors and, in imperfect labor markets, changes in unemployment and/or the size of the informal sector.

Consumption Prices. Self-employed workers are not the only people who consume. Employed workers, who are affected on the income side through changes in their wages and employment sector, are also affected by the changes in the relative prices of the goods they consume. Trade models often pay little heed to this channel because, if preferences are identical across individuals and homothetic, then changes in relative prices will affect all households equi-proportionately. But if preferences are not, in fact, homothetic, or if they differ across households, then the *shares* of different goods in their consumption bundles will vary, and relative price changes will affect different households differently. Under this channel, we also include changes in the *quality* of consumption goods available to consumers, either directly because of differences in quality between imported and domestically-produced goods, or because of improvements in domestic production as a result of import competition, or of the availability of imported inputs.

Taxes and Public Expenditures. As tariffs change so, in general, will tariff revenues. Although there is much evidence that it is possible to reduce protection in a revenue-neutral – or even revenue-enhancing – manner, if revenues do fall, then there will either be a decline in the level of some public service or transfer, or a rise in some other tax.[8] The incidence of these changes is entirely dependent on which expenditures or taxes are altered, and on their (marginal) incidence.

Ultimately, all trade reforms must affect household welfare – and its distribution – through one of these five primary channels. Much of the discussion in the literature has focused, however, on the nature of the mechanism through which tariff changes affect wages and employment levels. A trade reform that lowers tariffs for a number of goods may affect relative wages and the composition of employment through the standard Stolper-Samuelson channel, as described above, but it may also work in a number of different ways. These have been reviewed in some detail by Goldberg and Pavcnik (2004), and we provide only a sketch below:

- Trade liberalization may be accompanied by adjustments not only in the national composition of production, but in the *international* composition, with some activities being outsourced from developed to developing country locations. One hypothesis is that some of these activities are intensive in workers that are unskilled by rich-country criteria, but skilled in developing countries. See, for instance, Feenstra and Hanson (1996).

[8] The evidence suggests, however, that it has in many cases been possible to liberalize trade without loss in revenues. This may occur because non-tariff barriers generate rents for private agents, rather than government revenue; because some tariffs may initially be above their revenue-maximizing level; or because some trade reforms occur concomitantly with enhancements in the efficiency of customs agencies. See Ebrill *et al.* (1999) and the discussion in Winters *et al.* (2004).

- Technical change that raises firms' relative demand for skill is known as *skill-biased technical change* (SBTC). Whereas in developed countries SBTC is typically seen as a competing explanation (vis-à-vis trade openness) for increases in skill premiums, it has recently been argued that in developing countries, SBTC may be spurred on by trade liberalization. See Acemoglu (2003) and Theonig and Verdier (2003) for different models of how trade liberalization might lead to skill-biased technical change in developing countries. If indeed trade liberalization leads to changes in the relative demand for skilled and unskilled workers because of induced changes in technology, then this is a separate effect, additional to Stolper-Samuelson.

- Related to the previous two channels is the possibility that greater openness changes the *quality composition of domestic output*. Most goods (shoes, textiles, cars or computers) can be produced with very different quality, and there is some evidence that greater participation in world trade shifts production towards higher-quality goods in (at least some) domestic firms. This may be in response to greater import competition, or because exchange rate changes shifts resources from non-exporters to exporters. If higher-quality varieties are more intensive in skilled workers, this effect too could raise the relative demand for skills in the labor force. See Verhoogen (2008) and Shigeoka, Verhoogen and Wai-Poi (2006) for evidence from Mexico.

- Finally, wage levels for observably identical workers are not the same across different industries, either because of imperfect competition that gives rise to industry rents; or because of compensating differentials; or industry-specific skills. It is possible that tariff and mandated price changes affect these differentials, in addition to any impact they may have on the economy-wide skill premium. See, for example, Goldberg and Pavcnik (2005) on Colombia.

1.2.2. The Distributive Impact of Trade Liberalization in Latin America

Contrary to what was found in earlier LDC liberalization episodes, notably in East Asia, Latin American trade liberalizations during the 1980s and 1990s have been predominantly contemporaneous with *increases* in the economy-wide wage skill premium, which is typically defined as the ratio of wages of skilled workers to the wages of unskilled workers.[9] Although this ratio is not a particularly good measure of wage inequality, and certainly a very poor indicator of inequality in household incomes, it has been the focus of most empirical work.[10]

Evidence of a rising skills gap has been comprehensively established for Mexico, by Feenstra and Hanson (1995), Cragg and Epelbaum (1996), Feliciano (2001), and Hanson and Harrison (1999), among others. It has also been documented for Chile by Beyer, Rojas and Vergara (1999), for Colombia by Attanasio, Goldberg and Pavcnik (2004), and

[9] It matters whether skill levels are measured in practice by education levels (as typically done in studies based on household survey data) or by production vs. non-production workers (as commonly done in studies using firm-level data.

[10] Later in this paper, we investigate how changes in skill premium map into changes in more general measures of inequality.

for Costa Rica by Robbins and Grindling (1999). Given the presumption that developing countries are abundant in unskilled labor, the first reaction to these results was that it seemed to contradict the Stolper-Samuelson theorem, and considerable effort has been expended in proposing alternative explanations, many of which were described in general terms in the preceding subsection.

Wood (1997) argued that the simplest version of Stolper-Samuelson may not apply, because Latin American countries are perhaps abundant in land and natural resources, rather than unskilled labor; or because of the entry into the international trading system of countries even more unskilled-labor abundant, such as China and India. As discussed, Feenstra and Hanson (1995) suggested that part of the increase in the demand for skill in Mexico was due to outsourcing. Cragg and Epelbaum (1996) argued that it was driven by the increases in the returns to specific occupations, such as managers and administrators, who were highly skilled (rather than by returns to all skilled workers in the economy). Others have argued that greater openness has spurred a process of technological change that is skill-biased, as also discussed above. Attanasio, Goldberg and Pavcnik (2004) interpret their finding that increases in demand for skilled workers were largest for sectors with the largest tariff cuts as supporting the thesis of an endogenous skill-biased change in technology, that occurs in response to competitive pressures and to the availability of inputs brought about by greater openness.

Each of these alternative stories – occupational rewards, skill-biased technical change, quality upgrading, outsourcing – is plausible, and each is supported by at least some of the available evidence. But it is also true that an examination of the patterns of protection in Chile, Colombia and Mexico prior to liberalization reveals that tariffs were generally higher for industries intensive in unskilled labor (than for skill-intensive industries). In this case, a fall in the relative prices of these goods, and thus in the price of the factor they are intensive in, is perfectly in line with the Stolper-Samuelson theorem in the first place.[11]

Brazil was an exception, in that effective protection prior to liberalization was higher for skill-intensive industries. The correlation between tariffs and industry skill-shares in 1988 was mildly positive, and much stronger once tariffs are adjusted by the industry import penetration rates, which account for differences in the pass-through between tariffs and prices in different sectors.[12] Gonzaga *et al.* (2006) show that, as tariffs were (partly) harmonized between 1988 and 1995, the tariff and effective rates of protection (ERPs) declines for skill-intensive industries were greater than for industries intensive in unskilled workers. In accordance with Stolper-Samuelson predictions, the relative prices of skill-intensive goods then fell, as did the relative wages of more skilled workers. Using mandated wage equations, these authors estimate that the decline in the manufacturing skill premium over this period was of the order of 25 percent – larger than the actually observed 15 percent decline.

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[11] See Goldberg and Pavcnik (2004) for discussion.

[12] See Gonzaga *et al.* (2006) on the importance of this correction.

In addition, the pattern of labor reallocation was more consistent with a Stolper-Samuelson effect of trade liberalization, than with a Rybczynski-style effect of increases in the endowment of skilled labor: the manufacturing employment share of skilled workers rose by 2.67 percent, which decomposed into a 3.34 percent within-industries effect, and a negative 0.67 percent between industry effect. This contraction in the employment share of skill-intensive industries would not be expected if the dynamics were driven primarily by expansion in the endowment of skilled workers in Brazil, but is consistent with the expected employment reallocation in response to a trade shock.

The evidence presented by Gonzaga *et al.* (2006) strongly suggests that the Brazilian trade liberalization of 1988-1995 played some role in the decline of inequality in Brazil which began during that period. It appears to have done so through the classic channel of changes in the economy-wide skill premium, in line with the prediction of Hecksher-Ohlin trade theory, leading to a sizable decline in the wage gap between skilled and unskilled workers in manufacturing.[13]

But how important was this change in the skill premium for the actual size distribution of hourly wages in Brazil? There are two reasons why its importance is far from guaranteed: one is that skilled and unskilled workers are large and heterogeneous groupings. There is considerable wage variation within each group, and the two group distributions do overlap. The second reason is that Gonzaga *et al.* (2006) consider only

[13] The literature suggests that alternative channels of impact were less important. Pavcnik *et al.* (2004), for instance, find no evidence that changes in industry-specific wage premiums (or in skill-premiums specific to certain industries) changed in response to trade liberalization.

manufacturing workers, which accounted for 16 percent (13 percent) of total employment in 1988 (1995). Changes in their relative position vis-à-vis workers in agriculture (which were also affected by changes in tariffs) and in services (which were indirectly affected by changes in tariffs, and also by changes in the exchange rate) may have led to overall changes in wage inequality which are quite different from those mandated by the Stolper-Samuelson effects within manufacturing.

In the remainder of this chapter we examine two basic questions. First, we seek to place the changes in wage inequality which can be attributed to trade policy changes in the context of other changes that were concurrently affecting the wage distribution. Second, and more specifically, we also seek to quantify the contribution of the trade-mandated employment reallocation effects to changes in the wage distribution. A third, albeit more tentative, contribution is to investigate the implications of these trade-driven changes in the wage distribution for poverty and inequality in the distribution of household incomes per capita.

1.3. Data and Methodology

1.3.1 The Datasets

The data used in this study come from two different sources. The first of these is the household survey data with information on wages, hours of work, occupations, education levels, age, gender, race and location of workers. We use eleven waves of the *Pesquisa Nacional por Amostra de Domicílios* (PNAD), fielded by the *Instituto Brasileiro* *de Geografia e Estatística* (IBGE), annually between 1987 and 1999.[14] The PNAD is a nationally representative household survey, with a stratified and clustered sampling design which ensures coverage of rural and urban areas in every state of the federation, except for the rural areas of Acre, Amapá, Amazonas, Pará, Rondônia and Roraima.[15] Sample sizes varied somewhat from year to year, around approximately 300,000 individuals per year.

For our wage analysis, we considered all workers aged 15-65 who reported positive earnings during the survey's reference week. Since we are interested in quantifying the importance of trade and openness-related changes in explaining overall changes in the wage distribution, we include all workers, in agriculture, industry and services, regardless of formality or own-account status. Effective sample sizes for this analysis were 107,195 workers in 1998 and 123,455 workers in 1995. This is an important difference between our analysis and those of Gonzaga *et al.* (2006), or Pavcnik *et al.* (2004), who focus exclusively on workers in manufacturing.[16] The wage definition is hourly wages, calculated as a quarter of the monthly wage, divided by the number of hours worked on the average week. All monetary values are inflated to September 2004 prices, using the INPC deflator with the Corseuil and Fogel (2002) adjustment to

[14] There are eleven waves because the survey was not carried out in 1991 or 1994.

[15] These rural areas broadly correspond to the Amazon rainforest, which was excluded from PNAD sampling until 2003. Census data suggests that these areas account for 2.3 percent of the Brazilian population.

[16] The sample in Pavcnik *et al.* (2004) is, in addition, based on the Pesquisa Mensal de Emprego (PME) and is thus only representative of the country's six main metropolitan areas.

the 1994 index. See Ferreira *et al.* (2008) for the full deflator in each PNAD reference month.

As in all PNAD-based studies, we use years of schooling as our measure of a worker's skill.[17] In earnings regressions, we group workers into nine schooling groups: zero years, 1-3 years, 4 years, 5-7 years, 8 years (completed primary), 9-10 years (some high school), 11 years (completed high school), 12-14 years (some university), 15+ years (completed university). We also use this variable to construct a dichotomous skill indicator, classifying workers with 0-10 years of schooling as unskilled, and those with 11 or more (completed high school and above) as skilled. Earnings regressions were also estimated with an alternative indicator, which classified only workers with 15 years of schooling or more as skilled, and all results were qualitatively robust. Since workers with completed university accounted for 4.5 percent of the labor force in 1988, while workers with complete high school and above represented 16.4 percent, we chose the latter classification as more meaningful for Brazil. See Gonzaga *et al.* (2006) for a similar discussion of this classification.

The second data set used for this study comprises the trade-related variables for 22 industries, across the 1987-1999 period. Six trade-related variables are used: nominal tariffs and effective rates of protection come from Kume *et al.* (2000), as reported in

[17] Use of education to define a worker's skill is in fact common to most household or labor-force survey-based studies. Articles relying on firm-level data typically classify production workers as unskilled, and non-production workers as skilled. Although Slaughter (2000) shows that the two definitions do not seem to lead to very different conclusions in the US, Gonzaga *et al.* (2006) show that the distinction does matter for Brazil. Like the latter authors, we feel that the education classification is more appropriate in the Brazilian case, since trade liberalization and outsourcing of support activities led to considerable changes in the employment levels of non-productions workers during the period.

Table 1.1. Trade variables by industry, 1988 and 1995

	Nominal tariffs		ERP		Import penetration		Export share of production		M-RER		X-RER	
Industry	1988	1995	1988	1995	1988	1995	1988	1995	1988	1995	1988	1995
Agricultural products	17	7	15	8	na	na	na	na	5,347	7,351	110	193
Mining products	20	3	15	0	8	12	98	77	149	196	135	209
Oil and coal extraction	6	0	-3	-2	130	117	0	1	16	24	441	777
Non-metallic minerals	39	10	46	12	1	3	2	4	105	169	180	297
Steel, non-ferrous and other metallurgy products	33	11	37	14	3	7	28	28	92	131	6,021	8,158
Machinery and tractors	47	19	50	18	14	31	18	36	105	172	232	324
Electrical equipment, electronic equipment	50	21	59	30	12	18	7	10	56	86	114	182
Auto., trucks and buses; parts, comp. and other vehicles	43	31	45	74	9	16	13	12	91	147	296	414
Wood products and furniture	30	11	29	12	0	1	4	10	311	540	29	45
Cellulose, paper and printing	32	10	30	10	2	6	6	11	40	55	143	221
Rubber products	49	13	59	15	4	10	6	8	195	299	248	414
Chemical elements and products	66	15	76	16	56	87	33	39	30	46	118	189
Oil refining and petrochemicals	34	4	70	3	12	30	31	7	103	392	96	160
Pharmaceutical and perfumery products	45	8	52	8	6	13	2	3	45	73	208	346
Plastic products	57	15	72	21	2	7	2	3	60	92	311	435

Table 1.1. Trade variables by industry, 1988 and 1995 (cont.)

	Nominal tariffs		ERP		Import penetration		Export share of production		M-RER		X-RER	
Industry	1988	1995	1988	1995	1988	1995	1988	1995	1988	1995	1988	1995
Textile products	57	15	84	22	10	59	27	29	217	334	164	264
Apparel	76	20	94	24	0	3	1	2	162	253	109	185
Footwear	41	18	40	24	3	7	25	36	479	708	18	31
Processing of vegetal products	42	12	86	16	9	15	21	15	112	146	65	111
Meat packing, dairy industry, vegetal and other food products	63	20	73	21	3	7	50	47	52	83	85	140
Unclassified manufacturing	49	14	64	15	0	0	0	0	101	169	102	265
Simple average	44	17	52	21	19	28	22	22	390	566	456	652
Nontradable	0	0	0	0	0	0	0	0	67	104	91	147

Source: Nominal tariffs and effective rates of protection from Kume *et al.* (2000), reported in Abreu (2004); import penetration and export share of production from Muendler (2003); import- and export-weighted real exchange rates are authors' calculations from World Development Indicators (World Bank 2006) and COMTRADE (UN 2006). For more details, see Appendix.

Table 1.2. Industry Concordance

Trade Industry	PNAD Code	PNAD Industry	Final Code	Final Industry
Agricultural products	11-42	Various crops, horticulture and forestry	1	Agricultural products
Mining products	50, 53-59	Prospecting and extraction of non-oil/gas/coal minerals	2	Mining products
Oil and coal extraction	51-52	Oil, gas and coal	3	Oil and coal extraction
Non-metallic minerals	100	Non-metal processing	4	Non-metallic minerals
Steel products	110	Steel products	5	Steel, non-ferrous and other metal products
Non-ferrous metallurgy	110	Non-steel metals products	5	Steel, non-ferrous and other metal products
Other metallurgical products	110		5	Steel, non-ferrous and other metal products
Machinery and tractors	120	Manufacture of machines and equipment	6	Machinery and tractors
Electrical equipment	130	Manufacture of electrical and electronic equipment	7	Electrical and electronic equipment
Electronic equipment	130	Manufacture of electrical and electronic equipment	7	Electrical and electronic equipment
Automobiles, trucks and buses	140	Manufacture of vehicles and parts	8	Automobiles, trucks and buses; parts, comp. and other vehicles
Parts, components and other vehicles	140	Manufacture of vehicles and parts	8	Automobiles, trucks and buses; parts, comp. and other vehicles
Wood products and furniture	150, 151, 160	Manufacture of wood products and furniture	9	Wood products and furniture
Cellulose, paper and printing	170, 290	Pulp and paper products, printing and newspapers	10	Cellulose, paper and printing
Rubber products	180	Rubber products	11	Rubber products
Chemical elements	200	Chemical products	12	Chemical elements and products
Oil refining	201	Oil and petroleum products	13	Oil refining and petrochemicals

Table 1.2. Industry Concordance (cont.)

Trade Industry	PNAD Code	PNAD Industry	Final Code	Final Industry
Chemical products	200	Chemical products	12	Chemical elements and products
Pharmaceutical and perfumery products	210, 220	Pharmaceuticals and toiletries	14	Pharmaceutical and perfumery products
Plastic products	230	Plastics	16	Plastic products
Textile products	240, 241	Textiles	17	Textile products
Apparel	250	Apparel and clothing	18	Apparel
Footwear	251	Footwear	19	Footwear
Coffee industry			21	Meat packing, dairy industry, vegetal and other food products
Meat packing	260	Food preparation	21	Meat packing, dairy industry, vegetal and other food products
Dairy industry	260	Food preparation	21	Meat packing, dairy industry, vegetal and other food products
Sugar	17	Sugar cane extraction?	21	Meat packing, dairy industry, vegetal and other food products
Vegetal products	260		21	Meat packing, dairy industry, vegetal and other food products
Other food products	260, 261, 271	Other foods and drinks	21	Meat packing, dairy industry, vegetal and other food products
Other industries	300	Various scientific instruments	99	Unclassified manufacturing
	340-903	Construction, services, retail, finance, government etc.	22	Nontradable
Omitted	190	Leather and skins		
	202	Manufacture of synthetic materials (nylon etc)		

Abreu (2004); import penetration and export shares by industry come from Muendler (2003); and import-weighted and export-weighted industry-specific exchange rates were constructed by the authors, based on the methodology suggested by Goldberg (2004), and using data from the World Bank's World Development Indicators and the UN's COMTRADE.[18] Table 1.1 presents initial (1988) and terminal (1995) values for each of these variables for the 22 industries into which we have grouped Brazilian firms.[19] As in Pavcnik *et al.* (2004), our use of household survey and trade data with different industry definitions necessitated a concordance between the various datasets, mapping the more disaggregated industry classifications in the trade data to the broader PNAD classifications. In addition to the standard *Nível 80* to *Nível 100* concordance,[20] we developed concordances of our own. The main one is based on (but not identical to) Pavcnik *et al.* (2004), and is presented in Table 2.[21] A more detailed description of the steps taken to clean, construct and match the data is included in the data appendix.

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[18] As Goldberg (2004:1) notes, "At the national level, analyses of exchange rate moves often rely on aggregate trade-weighted exchange rates. However, aggregate indexes can be less effective than industry-specific indexes in capturing changes in industry competitive conditions induced by moves in specific bilateral exchange rates."

[19] Although we use data until 1999 in our estimation stage, the key initial and terminal years for our wage decomposition analysis are 1988 (at the onset of trade liberalization) and 1995 (the year in which it was completed.

[20] Available on Marc Muendler's excellent website of Brazilian data resources (http://www.econ.ucsd.edu/muendler/html/brazil.html). Nível 80 and 100 are official Brazilian industry classifications.

[21] We are grateful to Nina Pavcnik and Norbert Schady for graciously making the details of their concordance available to us. A further concordance between Nível 100 and the trade categories used by Kume *et al.* (2000) was also constructed, but is too detailed to present here.

1.3.2. Methodology

Since the objective is to understand and quantify the role of trade-induced changes in the wage distribution, in relation to the overall observed changes, we combine an extended version of the two-stage estimation framework which has recently been used to investigate the effect of trade reforms on wage premiums in a number of settings, with a more general decomposition of changes in the entire wage distribution. Following Pavcnik *et al.* (2004), our first stage regresses log hourly wages (w_{ij}) on a vector of worker *i*'s characteristics (including sex, race, experience, education, residential region, urban/rural status, household headship status, and formality status); a vector of industry *j* indicators (I_{ij}); and a set of interactions between industry indicators and skill category:[22]

$$\ln w_{ij} = X_{ij}\beta + I_{ij} * wp_j + (I_{ij} * S_{ij})sp_j + \varepsilon_{ij} \quad (1)$$

Equation 1 is estimated separately for each year in the data set, from 1987 to 1999. In addition to the wage equation, our first stage also includes a model of employment for each year in the sample, where an individual's occupation is regressed on a similar set (Z_{ij}) of personal characteristics, as well as whether or not he or she has children, and the spouse's occupational status. Given the polychotomous nature of the occupational choice, this relationship is estimated with a multinomial logit model:

[22] Recall, skilled workers are defined here as having completed high school or better (11+ years of education).

$$\Pr\{j=s\}=P^{s}(Z_i,\lambda)=\frac{e^{Z_i\lambda_s}}{e^{Z_i\lambda_s}+\sum_{j\neq s}e^{Z_i\lambda_j}} \tag{2}$$

In equation (2), there are ten possible occupational choices (j), corresponding to inactivity, unemployment, self-employment, employer status, and formal or informal employment in each of three broad sectors: agriculture, manufacturing and services. The full specification of models (1) and (2) is presented in the next section, alongside with results.

In the second stage, three sets of estimated coefficients from the first stage are pooled over time and regressed on a set of trade-related industry characteristics. The dependent variables in this stage are: (i) the industry premiums coefficients from (1), wp_{jt}; (ii) the industry-specific skill premiums coefficients from (1), sp_{jt}; and (iii) the constant terms λ_{0jt} for each occupation from (2). Each of these variables v_{jt} ={wp_{jt}; sp_{jt}; λ_{0jt}) is regressed (in first differences) on a set of trade-related variables (T_{jt}), including industry- specific effective rates of protection, import- and export-weighted exchange rates, import penetration and export shares:

$$\Delta v_{jt}=\Delta T_{jt}\gamma+\eta_{jt} \tag{3}$$

In addition to estimating a two-stage employment model, which we have not seen in the trade literature, there are other differences between these estimations and those reported in Pavcnik *et al.* (2004). Our data comes from a nationally representative household survey (the PNAD), and include workers in agriculture and non-tradable industries (for which industry-specific exchange rates can be constructed,[23] and affect relative prices). Rather than relying on the manufacturing sector in the six largest metropolitan areas of Brazil, our sample is therefore much more broadly representative of the country. Possibly as a result, some of our estimation results are different than those in Pavcnik *et al.* (2004), and we discuss them briefly in the next section.

But the main purpose of estimating equations (1)-(3) is to use them in the decomposition of all changes in the full wage distribution between 1988 and 1995. Following Juhn, Murphy and Pierce (1993) – henceforth cited as JMP – one can decompose the difference between the wage distribution prior to the liberalization (say, in 1988) and the wage distribution afterwards (say, in 1995) into three components: one due to changes in observed worker characteristics (X), one due to changes in the returns to those characteristics (measured by regression coefficients β), and a final one due to changes in the distribution of residuals (ε). Writing the distribution function of the residuals of equation (1) as $\vartheta_{it} = F_t(\varepsilon_{it})$, a standard JMP decomposition would proceed as follows.[24]

After estimating earnings regressions (like (1)) in both initial and terminal years:

$$\ln w_{i88} = X_{i88}\beta_{88} + F_{88}^{-1}(\theta_{i88}) \text{ and}$$

[23] We use economy-wide import- and export-weighted exchange rates for the non-tradable sector.

[24] We say 'a standard JMP decomposition' because there are variations on the basic theme. Alternative orderings could be used, or average coefficients instead of final year coefficients, etc. The specific interpretation varies, but the essence of the insight is the same.

$$\ln w_{i95} = X_{i95}\beta_{95} + F_{95}^{-1}(\theta_{i95}),$$

one would simulate two counterfactual wage distributions, as follows:

$$\ln w_i^a = X_{i88}\beta_{95} + F_{88}^{-1}(\theta_{i88}) \quad (4)$$

$$\ln w_i^b = X_{i88}\beta_{95} + F_{95}^{-1}(\theta_{i88}) \quad (5)$$

The difference between wage distributions $G(w_{88})$ and $G(w^a)$ would be interpreted as being due to differences in returns between the 1988 and 1995. The difference between $G(w^a)$ and $G(w^b)$ would be due to changes in the distribution of (or returns to) unobservable worker characteristics. Finally, the difference between $G(w_{95})$ and $G(w^b)$ would be due to changes in the joint distribution of observed worker characteristics (and their joint correlation with the residuals).[25]

Using our estimates of equations (1) – (3), we construct an expanded set of such counterfactual wage distributions, which also form an exact decomposition of the observed change between 1988 and 1995.[26] We construct six counterfactual wage distributions, chosen to shed light on different channels of effect from the trade-

[25] As noted by JMP, and in the closely related work of DiNardo *et al.* (1996) and Bourguignon *et al.* (2004), this is an accounting decomposition. Changes in the return structure are clearly causally related to changes in the distribution of characteristics (in more than one way). The decomposition exercise does not disentangle these causal relations, but provides a description of the observed changes.

[26] As in the original JMP decomposition, and indeed in any generalized Oaxaca-Blinder decomposition, the order of the simulations matter: the decomposition is path dependent. See Lemieux (2002) and Bourguignon *et al.* (2004) for discussions.

liberalization. Not all of the channels discussed in Section 1.2 are covered, but the key wage and employment channels are addressed.

Departing from equation (1), our first counterfactual is:

$$\ln w_{ij}^{1} = X_{ij}^{88}\beta^{88} + I_{ij}^{88} * wp_{j}^{s} + (I_{ij}^{88} * S_{ij}^{88})sp_{j}^{88} + F_{88}^{-1}\left(\theta_{i88}\right) \tag{6}$$

where $wp_{j}^{s} = \left(T_{j}^{95} - T_{j}^{88}\right)\hat{\gamma}_{wp}$ and $\hat{\gamma}_{wp}$ are the estimated coefficients in the second-stage regression (3) for the industry wage premiums. This first simulation therefore corresponds to changes in the wage distribution due only to those changes in industry wage premiums which are mandated by changes in the exogenous trade variables included in the second-stage equation (3). The second counterfactual is:

$$\ln w_{ij}^{2} = X_{ij}^{88}\beta^{88} + I_{ij}^{88} * wp_{j}^{s} + (I_{ij}^{88} * S_{ij}^{88})sp_{j}^{s} + F_{88}^{-1}\left(\theta_{i88}\right) \tag{7}$$

where $sp_{j}^{s} = \left(T_{j}^{95} - T_{j}^{88}\right)\hat{\gamma}_{sp}$ and $\hat{\gamma}_{sp}$ are the estimated coefficients in the second-stage regression (3) for industry-specific skill premiums. The third counterfactual is

$$\ln w_{ij}^{3} = X_{ij}^{88}\beta^{88} + I_{ij}^{s} * wp_{j}^{s} + (I_{ij}^{s} * S_{ij}^{88})sp_{j}^{s} + F_{88}^{-1}\left(\theta_{i88}\right) \tag{8}$$

where I_{ij}^{s} is a counterfactual vector of occupations, constructed by substituting $\lambda_{0j}^{s} = \left(T_{j}^{95} - T_{j}^{88}\right)\hat{\gamma}_{\lambda_0}$ into the occupational multinomial logit in equation (2), and then using it to predict the corresponding counterfactual distribution of occupations.[27] This

[27] As noted above, the ten occupational categories specified in equation 2 were more aggregated than the 22 industries for which wage and skill premiums are estimated. In constructing *G(w*^{3}*),* workers whose

third simulation therefore corresponds to the overall effect of industry premiums, industry-specific skill premiums and employment changes mandated by the second-stage trade variables, under the maintained functional form assumptions in (3).

The power of the preceding counterfactuals to simulate the changes in the wage distribution that arise from trade reforms depends entirely on the ability of the linear second stage equations to identify the impact of changes in tariffs and exchange rates on wage premiums and employment probabilities. They also miss, so far, a key theoretical channel through which a trade liberalization is likely to impact on wage differences in the economy, namely changes the *economy-wide* skill premium. After all, the wp_j and sp_j coefficients capture only changes in industry specific remuneration rates, controlling for changes in the average returns to education. Our fourth counterfactual is therefore:

$$\ln w_{ij}^{4} = X_{ij}^{88}\beta^{s} + I_{ij}^{s} * wp_{j}^{95} + (I_{ij}^{s} * S_{ij}^{88})sp_{j}^{95} + F_{88}^{-1}(\theta_{i88}) \tag{9}$$

where $\beta^{s} = \{\beta_{ed}^{95};\beta_{-ed}^{88}\}$. The difference between (9) and (8) is twofold: the industry and industry-specific skill premium coefficients mandated by the second stage are replaced with those estimated in 1995, and the economy-wide returns on schooling coefficient is replaced with its 1995 value. This simulation therefore corresponds to a 'more generous' estimate of the 'price effects' of trade liberalization, in which the full changes

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predicted occupations differed from those observed in 1988 due to changes in λ_{0j} were allocated to specific industries (within the broad sector to which they were mapped by the multinomial logit) by random draws with probabilities derived from the 1995 employment distribution across industries.

in returns to education and to industry membership – rather than only those mandated by the second stage – are included. Although the main channel through which trade reforms might affect β_{ed}^{95} is the Stolper-Samuelson effect of reduced protection in skill-intensive industries, there may be other channels too. If one is prepared to accept that skill-biased technical change in Brazil, or skill-demanding changes in the quality composition of domestic output, are endogenous to trade liberalization, as discussed in Section 1.2, then one may come closer to the view that all changes in the returns to schooling between 1988 and 1995 are, in some way or another, related to trade. Be that as it may, we see this particular counterfactual wage distribution as a generous estimate of the joint wage and employment effects of trade on the wage distribution. The true contribution of trade liberalization to changes in Brazilian inequality is likely to lie somewhere between the changes accumulated up to equation (8) and those corresponding to (9).

Three remaining steps (and two counterfactual distributions) complete the decomposition – and represent changes that are less likely to have been driven by trade reforms. The first of these (in equation 10) computes the additional changes in the structure of returns to observed characteristics (like experience, location, race, gender, etc.). The second (in equation 11), brings in the distribution of residuals from 1995, in a rank-preserving transformation:

$$\ln w_{ij}^{5} = X_{ij}^{88}\beta^{95} + I_{ij}^{s} * wp_{j}^{95} + (I_{ij}^{s} * S_{ij}^{88})sp_{j}^{95} + F_{88}^{-1}\left(\theta_{i88}\right) \tag{10}$$

$$\ln w_{ij}^{6} = X_{ij}^{88}\beta^{95} + I_{ij}^{s} * wp_{j}^{95} + (I_{ij}^{s} * S_{ij}^{88})sp_{j}^{95} + F_{95}^{-1}(\theta_{i88}) \tag{11}$$

Finally, the difference between (11) and the equation estimated for 1995:

$$\ln w_{ij}^{95} = X_{ij}^{95}\beta^{95} + I_{ij}^{95} * wp_{j}^{95} + (I_{ij}^{95} * S_{ij}^{95})sp_{j}^{95} + F_{95}^{-1}(\theta_{i95}) \tag{12}$$

corresponds to differences in the joint distribution of observed characteristics between 1995 and 1988 (except for the changes in occupational structure due to trade, which had been predicted in equation 8). This step also accounts for changes in the correlation between the observed characteristics and the residual terms, including any changes in selection into the labor force.

Only equation (1), for 1988, and equation (12), for 1995 are estimated on observed data. Equations (6)-(11) give rise to simulated wage distributions $G(w^1)$ and $G(w^6)$. In Section 1.5, simulation results are presented in two ways. First, a number of inequality indicators are computed for each counterfactual distribution, so that we can decompose the observed changes between 1988 and 1995 into the components corresponding to each counterfactual. Second, we can see a fully disaggregated picture by plotting the observed wage growth incidence curve between 1988 and 1995, $g(p) = \left(w_p^{95} - w_p^{88}\right)/w_p^{88}$, and presenting each intermediate counterfactual growth incidence curve: $g^s(p) = \left(w_p^{s} - w_p^{88}\right)/w_p^{88}$, s = 1, …,6.[28]

[28] The 'wage growth incidence curve' is an application to the distribution of wages of Ravallion and Chen's 2003 concept of the growth incidence curve, which those authors originally defined on the distribution of household incomes or expenditures.

1.4 Estimation Results

Before we turn to the simulation results in the next section, this section presents the estimation results on which they build. Table 1.3a presents the main first-stage results for the wage equation (1), while Tables 1.3b and 1.3c report the industry-specific wage and skill premiums coefficient estimates respectively. Each model was estimated for each year in the 1987-1999 interval for which data were available. The results in Table 1.3a are in line with existing analysis of the Brazilian labor market (see e.g. Ferreira and Barros 1999). There are large and significant returns to education, and smaller and concave returns to experience. Measured with respect to zero years of schooling, returns to education fell consistently over the period. This decline was most pronounced for intermediate education categories (4-10 years of schooling). Returns to experience have also fallen. There is a substantial male wage premium, which has also been declining. In contrast, racial premiums of both whites and Asians with respect to Afro-Brazilians have persisted or increased. Controlling for other observed characteristics, employers, the self-employed and formal employees all earn more than informally employed workers. Metropolitan and urban location premiums vis-à-vis rural workers of identical characteristics have also fallen over the period, though they remain statistically significant. All specifications also include industry and interacted industry-skill indicators, the coefficients on which are reported in Tables 1.3b and 1.3c. These coefficients are then pooled and regressed on a vector of trade variables in the second stage.

Table 1.3a. First Stage Regression Results: Wages

	1987	1988	1989	1990	1992	1993
Male	0.321	0.32	0.336	0.297	0.249	0.271
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.006)***	(0.006)***
Experience	0.048	0.047	0.045	0.044	0.038	0.039
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Experience squared	-0.001	-0.001	-0.001	-0.001	0	0
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
White	0.135	0.143	0.185	0.157	0.139	0.153
	(0.005)***	(0.005)***	(0.006)***	(0.005)***	(0.005)***	(0.005)***
Yellow	0.294	0.318	0.319	0.303	0.264	0.348
	(0.035)***	(0.038)***	(0.044)***	(0.038)***	(0.042)***	(0.040)***
1-3 years education	0.213	0.19	0.203	0.195	0.143	0.172
	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***
4 years education	0.393	0.4	0.398	0.392	0.324	0.356
	(0.009)***	(0.010)***	(0.010)***	(0.009)***	(0.009)***	(0.009)***
5-7 years education	0.578	0.582	0.573	0.561	0.463	0.496
	(0.011)***	(0.011)***	(0.011)***	(0.011)***	(0.010)***	(0.010)***
Completed primary	0.815	0.812	0.806	0.767	0.666	0.709
	(0.012)***	(0.013)***	(0.013)***	(0.012)***	(0.011)***	(0.012)***
9-10 years education	0.955	0.967	0.981	0.944	0.82	0.848
	(0.015)***	(0.015)***	(0.016)***	(0.015)***	(0.014)***	(0.014)***
Completed high school	1.23	1.274	1.224	1.096	0.933	1.047
	(0.058)***	(0.060)***	(0.061)***	(0.049)***	(0.047)***	(0.049)***
12-14 years education	1.623	1.691	1.656	1.511	1.283	1.426
	(0.060)***	(0.062)***	(0.063)***	(0.051)***	(0.049)***	(0.052)***
Completed university	2.05	2.147	2.05	1.915	1.649	1.82
	(0.059)***	(0.061)***	(0.062)***	(0.050)***	(0.049)***	(0.051)***

Table 1.3a. First Stage Regression Results: Wages (cont.)

	1987	1988	1989	1990	1992	1993
Formal employee	0.22	0.333	0.237	0.17	0.401	0.357
	(0.006)***	(0.006)***	(0.006)***	(0.006)***	(0.006)***	(0.006)***
Self-employed	0.274	0.295	0.338	0.319	0.302	0.337
	(0.008)***	(0.008)***	(0.008)***	(0.008)***	(0.007)***	(0.008)***
Employer	0.966	0.974	1.07	0.938	0.925	0.972
	(0.018)***	(0.019)***	(0.017)***	(0.015)***	(0.016)***	(0.016)***
Northeast region	-0.369	-0.353	-0.441	-0.443	-0.291	-0.404
	(0.009)***	(0.010)***	(0.010)***	(0.010)***	(0.011)***	(0.011)***
Southeast region	-0.077	-0.025	-0.092	-0.124	0.097	-0.021
	(0.009)***	(0.009)***	(0.010)***	(0.009)***	(0.010)***	(0.010)**
South region	-0.146	-0.107	-0.16	-0.165	0.063	0.026
	(0.010)***	(0.011)***	(0.011)***	(0.011)***	(0.011)***	(0.011)**
Central West region	-0.019	-0.005	-0.079	-0.045	0.055	0.068
	(0.010)*	-0.01	(0.011)***	(0.010)***	(0.011)***	(0.011)***
Metropolitan residence	0.319	0.331	0.328	0.313	0.302	0.307
	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***
Urban residence	0.198	0.127	0.146	0.158	0.135	0.145
	(0.008)***	(0.009)***	(0.009)***	(0.008)***	(0.009)***	(0.009)***
Head of household	0.208	0.203	0.193	0.189	0.159	0.166
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.006)***	(0.006)***
Industry indicators	Yes	Yes	Yes	Yes	Yes	Yes
Industry * skill indicators	Yes	Yes	Yes	Yes	Yes	Yes
Observations	112,655	112,730	114,961	116,882	118,075	119,949
R-squared	0.59	0.59	0.57	0.58	0.55	0.55

Table 1.3a. First Stage Regression Results: Wages (cont.)

	1995	1996	1997	1998	1999
Male	0.222	0.214	0.228	0.214	0.216
	(0.006)***	(0.006)***	(0.006)***	(0.006)***	(0.005)***
Experience	0.036	0.036	0.036	0.034	0.035
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Experience squared	0	0	0	0	0
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
White	0.156	0.165	0.165	0.159	0.161
	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.004)***
Yellow	0.346	0.398	0.439	0.351	0.285
	(0.040)***	(0.043)***	(0.046)***	(0.035)***	(0.040)***
1-3 years education	0.145	0.146	0.14	0.144	0.124
	(0.008)***	(0.009)***	(0.009)***	(0.008)***	(0.008)***
4 years education	0.307	0.304	0.288	0.281	0.266
	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.009)***
5-7 years education	0.436	0.406	0.41	0.398	0.373
	(0.009)***	(0.010)***	(0.009)***	(0.009)***	(0.009)***
Completed primary	0.628	0.605	0.602	0.586	0.547
	(0.011)***	(0.011)***	(0.011)***	(0.010)***	(0.010)***
9-10 years education	0.746	0.741	0.726	0.705	0.664
	(0.013)***	(0.013)***	(0.012)***	(0.012)***	(0.012)***
Completed high school	0.968	1.002	1.001	0.938	0.896
	(0.047)***	(0.047)***	(0.047)***	(0.046)***	(0.041)***
12-14 years education	1.39	1.439	1.404	1.35	1.307
	(0.049)***	(0.049)***	(0.049)***	(0.048)***	(0.043)***
Completed university	1.791	1.824	1.814	1.761	1.738
	(0.048)***	(0.049)***	(0.048)***	(0.047)***	(0.042)***

Table 1.3a. First Stage Regression Results: Wages (cont.)

	1995	1996	1997	1998	1999
Formal employee	0.184	0.182	0.198	0.207	0.228
	(0.005)***	(0.006)***	(0.005)***	(0.005)***	(0.005)***
Self-employed	0.257	0.268	0.205	0.184	0.197
	(0.007)***	(0.007)***	(0.007)***	(0.007)***	(0.006)***
Employer	0.938	0.903	0.908	0.853	0.876
	(0.014)***	(0.016)***	(0.014)***	(0.014)***	(0.014)***
Northeast region	-0.29	-0.276	-0.296	-0.228	-0.244
	(0.010)***	(0.010)***	(0.010)***	(0.010)***	(0.009)***
Southeast region	0.072	0.105	0.1	0.13	0.112
	(0.010)***	(0.010)***	(0.009)***	(0.009)***	(0.009)***
South region	-0.003	0.013	0.034	0.055	0.02
	-0.01	-0.011	(0.010)***	(0.010)***	(0.010)**
Central West region	0.014	0.055	0.047	0.064	0.042
	-0.01	(0.011)***	(0.010)***	(0.010)***	(0.010)***
Metropolitan residence	0.321	0.326	0.317	0.295	0.252
	(0.008)***	(0.009)***	(0.008)***	(0.008)***	(0.008)***
Urban residence	0.157	0.15	0.122	0.108	0.091
	(0.008)***	(0.008)***	(0.008)***	(0.007)***	(0.007)***
Head of household	0.175	0.17	0.156	0.156	0.149
	(0.006)***	(0.006)***	(0.005)***	(0.005)***	(0.005)***
Industry indicators	Yes	Yes	Yes	Yes	Yes
Industry * skill indicators	Yes	Yes	Yes	Yes	Yes
Observations	128,360	124,017	131,202	129,719	133,310
R-squared	0.56	0.54	0.56	0.56	0.56

Notes: Robust standard errors in parentheses.
* significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.
Dependent variable is real hourly wage from principal job. Regions are relative to north region. White and yellow are relative to black. Education-attainment indicators are relative to no education. Informal employee and self-employed coefficients are relative to formal employees.

Table 1.3b: First Stage Regression Results: Industry Wage Premiums

Industry	1987	1988	1989	1990	1992	1993
Mining products	0.514	0.578	0.488	0.433	0.238	0.315
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Oil and coal extraction	0.678	0.666	0.680	0.727	0.835	0.874
	(0.009)	(0.011)	(0.010)	(0.011)	(0.013)	(0.018)
Non-metallic minerals	0.202	0.203	0.225	0.242	0.188	0.191
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Steel, non-ferrous and other metallurgy products	0.398	0.398	0.373	0.458	0.381	0.378
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Machinery and tractors	0.538	0.539	0.520	0.636	0.406	0.473
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Electrical equipment, electronic equipment	0.467	0.493	0.450	0.614	0.507	0.404
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Auto., trucks and buses; parts, comp. and other vehicles	0.509	0.608	0.529	0.680	0.646	0.590
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wood products and furniture	0.035	0.020	0.041	0.157	0.091	0.131
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Cellulose, paper and printing	0.325	0.382	0.328	0.437	0.410	0.343
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rubber products	0.480	0.536	0.325	0.515	0.293	0.387
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)

Table 1.3b: First Stage Regression Results: Industry Wage Premiums (cont.)

Industry	1987	1988	1989	1990	1992	1993
Chemical elements and products	0.410	0.326	0.300	0.394	0.383	0.288
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Oil refining and petrochemicals	0.563	0.709	0.600	0.571	0.696	0.677
	(0.010)	(0.008)	(0.011)	(0.007)	(0.007)	(0.009)
Pharmaceutical and perfumery products	0.343	0.418	0.294	0.396	0.431	0.445
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Plastic products	0.360	0.364	0.382	0.465	0.315	0.317
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Textile products	0.153	0.239	0.207	0.253	0.195	0.223
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Apparel	0.267	0.310	0.334	0.482	0.267	0.259
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Footwear	0.210	0.121	0.278	0.412	0.253	0.176
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Processing of vegetal products	0.306	0.360	0.192	0.276	0.522	0.408
	(0.013)	(0.008)	(0.014)	(0.008)	(0.008)	(0.011)
Meat packing, dairy industry, vegetal and other food products	0.151	0.169	0.166	0.270	0.180	0.225
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unclassified manufacturing	0.068	0.065	0.100	0.160	0.080	0.071
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nontradable	0.164	0.149	0.149	0.300	0.184	0.171
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 1.3b: First Stage Regression Results: Industry Wage Premiums (cont.)

Industry	1995	1996	1997	1998	1999
Mining products	0.316	0.213	0.347	0.393	0.349
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Oil and coal extraction	0.817	1.043	0.677	0.824	0.994
	(0.012)	(0.018)	(0.019)	(0.013)	(0.018)
Non-metallic minerals	0.274	0.269	0.353	0.353	0.314
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Steel, non-ferrous and other metallurgy products	0.476	0.484	0.494	0.492	0.432
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Machinery and tractors	0.516	0.508	0.562	0.504	0.495
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Electrical equipment, electronic equipment	0.551	0.503	0.611	0.577	0.458
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Auto., trucks and buses; parts, comp. and other vehicles	0.685	0.692	0.662	0.657	0.628
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wood products and furniture	0.274	0.299	0.290	0.303	0.298
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cellulose, paper and printing	0.484	0.456	0.512	0.490	0.466
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Rubber products	0.553	0.665	0.433	0.394	0.473
	(0.003)	(0.005)	(0.002)	(0.005)	(0.005)

Table 1.3b: First Stage Regression Results: Industry Wage Premiums (cont.)

Industry	1995	1996	1997	1998	1999
Chemical elements and products	0.421	0.421	0.458	0.403	0.454
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Oil refining and petrochemicals	0.532	0.508	0.566	0.511	0.554
	(0.008)	(0.007)	(0.004)	(0.005)	(0.011)
Pharmaceutical and perfumery products	0.434	0.485	0.565	0.533	0.521
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Plastic products	0.423	0.375	0.425	0.435	0.374
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Textile products	0.321	0.285	0.386	0.338	0.184
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Apparel	0.331	0.317	0.380	0.342	0.310
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Footwear	0.249	0.268	0.271	0.209	0.237
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Processing of vegetal products	0.640	0.477	0.426	0.446	0.174
	(0.007)	(0.010)	(0.005)	(0.014)	(0.006)
Meat packing, dairy industry, vegetal and other food products	0.298	0.316	0.328	0.331	0.277
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unclassified manufacturing	0.095	0.196	0.159	0.147	0.103
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Nontradable	0.306	0.328	0.371	0.367	0.327
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Robust standard errors in parentheses.

Table 1.3c: First Stage Regression Results: Industry Skill Premiums

Industry	1987	1988	1989	1990	1992	1993
Mining products	0.089	0.108	0.267	0.400	0.462	-0.052
	(0.018)	(0.013)	(0.010)	(0.014)	(0.015)	(0.018)
Oil and coal extraction	0.465	0.411	0.537	0.495	0.293	0.202
	(0.020)	(0.022)	(0.021)	(0.029)	(0.023)	(0.030)
Non-metallic minerals	0.123	0.184	0.162	0.090	0.144	0.130
	(0.008)	(0.011)	(0.013)	(0.009)	(0.009)	(0.008)
Steel, non-ferrous and other metallurgy products	0.030	-0.071	0.096	0.125	0.148	0.132
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)
Machinery and tractors	-0.080	-0.119	-0.121	0.020	0.218	0.082
	(0.006)	(0.008)	(0.008)	(0.006)	(0.005)	(0.007)
Electrical equipment, electronic equipment	0.082	0.073	0.069	0.113	0.039	0.104
	(0.006)	(0.007)	(0.007)	(0.005)	(0.007)	(0.006)
Auto., trucks and buses; parts, comp. and other vehicles	-0.007	-0.018	-0.072	-0.014	0.113	0.253
	(0.006)	(0.007)	(0.007)	(0.005)	(0.006)	(0.006)
Wood products and furniture	-0.051	0.036	-0.125	0.121	0.050	0.020
	(0.010)	(0.009)	(0.009)	(0.007)	(0.006)	(0.007)
Cellulose, paper and printing	-0.046	-0.131	0.000	0.046	0.006	-0.079
	(0.006)	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)
Rubber products	-0.025	-0.273	0.054	-0.136	0.109	0.337
	(0.032)	(0.029)	(0.022)	(0.026)	(0.025)	(0.015)

Table 1.3c: First Stage Regression Results: Industry Skill Premiums (cont.)

Industry	1987	1988	1989	1990	1992	1993
Chemical elements and products	0.155	0.175	0.223	0.282	0.254	0.327
	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)	(0.007)
Oil refining and petrochemicals	0.456	0.216	0.074	0.374	0.287	0.201
	(0.019)	(0.015)	(0.026)	(0.015)	(0.017)	(0.016)
Pharmaceutical and perfumery products	0.088	-0.057	0.184	0.211	0.193	0.078
	(0.011)	(0.012)	(0.015)	(0.012)	(0.011)	(0.012)
Plastic products	0.050	0.110	-0.080	0.170	0.125	-0.084
	(0.018)	(0.014)	(0.022)	(0.010)	(0.010)	(0.011)
Textile products	-0.002	0.153	0.086	0.117	0.235	0.145
	(0.010)	(0.009)	(0.009)	(0.007)	(0.007)	(0.008)
Apparel	-0.185	-0.288	-0.224	-0.116	-0.160	-0.242
	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)	(0.005)
Footwear	-0.058	-0.062	-0.024	0.061	-0.105	-0.113
	(0.019)	(0.015)	(0.018)	(0.009)	(0.010)	(0.010)
Processing of vegetal products	0.126	0.024	-0.069	0.329	0.242	0.001
	(0.025)	(0.041)	(0.024)	(0.031)	(0.023)	(0.022)
Meat packing, dairy industry, vegetal and other food products	0.000	-0.009	0.019	0.010	0.125	-0.003
	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Unclassified manufacturing	0.110	0.056	0.282	0.357	0.233	0.035
	(0.008)	(0.012)	(0.010)	(0.008)	(0.006)	(0.006)
Nontradable	0.194	0.141	0.185	0.265	0.204	0.158
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)

Table 1.3c: First Stage Regression Results: Industry Skill Premiums (cont.)

Industry	1995	1996	1997	1998	1999
Mining products	0.163	0.258	0.180	0.326	0.220
	(0.014)	(0.017)	(0.013)	(0.011)	(0.012)
Oil and coal extraction	0.151	0.039	0.380	0.143	0.081
	(0.022)	(0.031)	(0.032)	(0.028)	(0.025)
Non-metallic minerals	0.225	0.184	0.059	0.044	0.107
	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)
Steel, non-ferrous and other metallurgy products	0.090	-0.020	0.000	0.037	0.051
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Machinery and tractors	0.050	-0.008	-0.014	0.036	0.001
	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
Electrical equipment, electronic equipment	0.093	-0.035	-0.052	0.031	0.096
	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)
Auto., trucks and buses; parts, comp. and other vehicles	0.020	-0.104	-0.010	0.056	0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Wood products and furniture	-0.008	-0.179	-0.218	-0.059	-0.143
	(0.007)	(0.006)	(0.006)	(0.005)	(0.003)
Cellulose, paper and printing	0.032	-0.069	-0.067	0.005	-0.067
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Rubber products	0.158	-0.018	0.179	0.258	-0.197
	(0.017)	(0.021)	(0.024)	(0.015)	(0.021)

Table 1.3c: First Stage Regression Results: Industry Skill Premiums (cont.)

Industry	1995	1996	1997	1998	1999
Chemical elements and products	0.225	0.173	0.139	0.156	0.073
	(0.005)	(0.007)	(0.006)	(0.008)	(0.005)
Oil refining and petrochemicals	0.294	0.215	0.380	0.308	0.250
	(0.017)	(0.017)	(0.013)	(0.012)	(0.018)
Pharmaceutical and perfumery products	0.243	0.152	-0.052	0.111	0.066
	(0.011)	(0.010)	(0.011)	(0.008)	(0.007)
Plastic products	0.133	0.074	0.055	-0.030	0.043
	(0.011)	(0.010)	(0.010)	(0.008)	(0.006)
Textile products	0.181	0.143	-0.099	0.002	0.123
	(0.007)	(0.009)	(0.007)	(0.008)	(0.006)
Apparel	-0.230	-0.289	-0.119	-0.194	-0.135
	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)
Footwear	-0.155	-0.084	-0.157	-0.054	-0.153
	(0.010)	(0.012)	(0.009)	(0.007)	(0.006)
Processing of vegetal products	-0.280	0.117	0.229	0.257	0.332
	(0.047)	(0.022)	(0.032)	(0.032)	(0.017)
Meat packing, dairy industry, vegetal and other food products	0.069	-0.064	-0.006	0.016	0.032
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Unclassified manufacturing	0.232	0.081	0.140	0.137	0.167
	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
Nontradable	0.130	0.055	0.053	0.095	0.101
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: Robust standard errors in parentheses.

Table 1.4a reports the first-stage results for the employment model in (2), as marginal effects of unit changes in each independent variable, with all other variables held at their mean values. These estimates are also mostly in line with expectations. Workers with more experience and education are less likely to be employed in agriculture or informally. In addition, those with higher education are also more likely to be employers, as are whites and Asians, and to work in the formal non-tradable sector, presumably often as professionals. We also see some evidence over time of more females entering the labor force. While men are more likely to be working, the male coefficient falls between 1988 and 1995 across most industries. The industry constants, which are pooled and used in the second stage, are summarized in Table 1.4b.

One concern that is typically voiced with respect to multinomial logit models such as (2) is that they assume that the odds ratios of any two possibilities (p_j/p_k) are independent of the number and nature of alternative outcomes. This is known as the independence of irrelevant alternatives (IIA) hypothesis. When alternative polychotomous discrete choice models that do not make this assumption, such as multinomial probits, are unstable or display convergence problems, one can test for the validity of the assumption using, for instance, the Hausman specification test which, in essence, tests for the stability of parameter estimates as alternative outcomes are excluded from the model. This test failed to reject the null hypothesis (that IIA is satisfied) for 8 out of our 9 outcome categories for 1995. Although results were poorer for 1988, with four rejections of the null, the overall picture is not one of overwhelming rejection of the Multinomial Logit specification.[29]

Table 1.5 reports the second-stage regression of industry wage premiums on effective rates of protection, import penetration, export shares, and import- and export-weighted real exchange rates. All specifications are in first-differences. Import penetration rates and export shares are entered only in lags, so as to reduce possible simultaneity concerns. The basic argument for treating changes in effective rates of protection – the main variable of interest – as exogenous is the same as in Attanasio, Goldberg and Pavcnik (2004) and Pavcnik *et al.* (2004): trade reforms in Latin America in the late 1980s and early 1990s arose as a response to becoming GATT / WTO members, or to a central policy decision to comply with previously negotiated rules. “This reflects the government’s objective to reduce tariffs across industries to more uniform rates negotiated with the WTO. Policymakers accordingly cater less to special lobby interests, so that tariff declines in each industry are proportional to the industry’s pre-reform tariff levels (…) alleviating concerns about endogeneity at least in the economic sense” (Goldberg and Pavcnik 2004:4)

[29] Details from the Hausman specification test are available from the authors on request.

Table 1.4a. First-stage regression results, 1988 and 1995 employment multinomial logit: marginal effects

	Not economic-ally active	Unemployed	Self-employed (all industries)	Agriculture	
				Informal	Formal
			1988		
Column	0	1	2	3	4
Probability (at mean)	0.329	0.026	0.186	0.046	0.013
Male		0.009 ***	0.137 ***	0.091 ***	0.025 ***
Experience		0.001 ***	0.004 ***	-0.001 ***	-0.000 ***
Experience squared		-0.000 ***	-0.000 ***	0.000 ***	-0.000 ***
White		-0.007 ***	0.012 ***	-0.014 ***	-0.001 ***
Yellow		-0.030 ***	0.092 *	0.042 **	-0.032 ***
1-3 years education		0.006 ***	-0.012	-0.029 ***	-0.003 ***
4 years education		0.005 ***	-0.009 ***	-0.055 ***	-0.008 ***
5-7 years education		0.013 ***	-0.048 ***	-0.088 ***	-0.013 ***
Completed primary		0.012 ***	-0.043 **	-0.119 ***	-0.018 ***
9-10 years education		0.008 ***	-0.070 ***	-0.129 ***	-0.026 ***
Completed high school		0.018 ***	-0.073	-0.131 ***	-0.017 ***
12-14 years education		0.001	-0.122 ***	-0.188 ***	-0.033 ***
Completed university		0.008 ***	-0.038 ***	-0.132 ***	-0.017 *
Region 2		0.008 ***	-0.012	0.026 ***	0.014 ***
Region 3		0.004 ***	-0.085 ***	0.035 ***	0.029 ***
Region 4		0.008 ***	-0.021 ***	0.011 ***	0.023 ***
Region 5		0.000	-0.051 ***	0.038 ***	0.021 ***
Metropolitan residence		0.032 ***	-0.202 ***	-0.162 ***	-0.040 ***
Urban residence		0.025 ***	-0.197 ***	-0.069 ***	-0.018 ***
Head of household		0.003 ***	0.094 ***	0.014 ***	0.014 ***
Children 0-14 years in household		-0.003 ***	-0.011 ***	-0.000 ***	0.000 **
Has a spouse who works		-0.972 ***	1.870 ***	0.439 ***	0.124
Observations	177,376	177,376	177,376	177,376	177,376

Table 1.4a. First-stage regression results, 1988 and 1995 employment multinomial logit: marginal effects (cont.)

	Manufacturing		Non-tradable sector		
	Informal	Formal	Informal	Formal	Employer (all industries)
			1988		
Column	5	6	7	8	9
Probability (at mean)	0.016	0.080	0.108	0.173	0.022
Male	0.016 ***	0.081 ***	-0.009 ***	0.086 ***	0.032 ***
Experience	-0.001	0.008 ***	-0.009 ***	0.014 ***	0.004 ***
Experience squared	0.000 ***	-0.000 ***	0.000 ***	-0.000 ***	-0.000 ***
White	-0.001 ***	0.004 ***	-0.030 ***	-0.026 ***	0.014 ***
Yellow	0.003	0.005	-0.098 ***	-0.076 ***	0.022 ***
1-3 years education	-0.000	0.019 ***	0.007 ***	0.031 ***	0.012 ***
4 years education	-0.001	0.039 ***	-0.002 ***	0.064 ***	0.023 ***
5-7 years education	-0.003	0.047 ***	0.003 ***	0.088 ***	0.029 ***
Completed primary	-0.005 **	0.051 ***	-0.005	0.129 ***	0.039 ***
9-10 years education	-0.009 ***	0.042 ***	-0.010	0.164 ***	0.042 ***
Completed high school	-0.011 **	0.055 ***	0.032 ***	0.221 ***	0.051 ***
12-14 years education	-0.012 ***	0.045 ***	0.078 ***	0.228 ***	0.054 ***
Completed university	-0.012	0.053 ***	0.116 ***	0.237 ***	0.057 ***
Region 2	0.000	-0.013 **	-0.002	-0.002	-0.001
Region 3	-0.004	0.064 ***	-0.002 ***	0.024 ***	0.001 ***
Region 4	-0.007	0.059 ***	-0.020 ***	0.054 ***	-0.000 ***
Region 5	0.000	-0.047 ***	0.020 ***	0.043 ***	0.003 ***
Metropolitan residence	0.006 ***	0.099 ***	0.072 ***	0.190 ***	-0.012 ***
Urban residence	0.003 ***	0.066 ***	0.082 ***	0.139 ***	-0.006 ***
Head of household	0.006 ***	0.081 ***	0.065 ***	0.144 ***	0.029 ***
Children 0-14 years in household	-0.001 ***	-0.014 ***	-0.004 ***	-0.042 ***	-0.002 ***
Has a spouse who works	0.158 ***	0.753 ***	1.032 ***	1.659 ***	0.217 ***
Observations	177,376	177,376	177,376	177,376	177,376

Table 1.4a. First-stage regression results, 1988 and 1995 employment multinomial logit: marginal effects (cont.)

	Not economic-ally active	Unemployed	Self-employed (all industries)	Agriculture	
				Informal	Formal
			1995		
Column	0	1	2	3	4
Probability (at mean)	0.308	0.046	0.203	0.034***	0.013
Male		-0.004 ***	0.159 ***	0.072 ***	0.025 ***
Experience		0.000 ***	0.008 ***	-0.000 ***	0.000 ***
Experience squared		-0.000 ***	-0.000 ***	-0.000 ***	-0.000 ***
White		-0.007 ***	0.023	-0.013 ***	-0.001 ***
Yellow		-0.029 ***	0.113 ***	0.015	-0.005
1-3 years education		-0.001 ***	0.003 ***	-0.022 ***	-0.004 ***
4 years education		-0.002 ***	0.001 ***	-0.039 ***	-0.009 ***
5-7 years education		0.006 ***	-0.015 ***	-0.062 ***	-0.013 ***
Completed primary		0.008 ***	-0.017 ***	-0.080 ***	-0.026 ***
9-10 years education		0.008 ***	-0.042 *	-0.095 ***	-0.030 ***
Completed high school		0.005 ***	-0.028 ***	-0.103 ***	-0.027 ***
12-14 years education		-0.003 ***	-0.047 ***	-0.149 ***	-0.036 ***
Completed university		-0.008 ***	-0.015 ***	-0.095 ***	-0.026 ***
Region 2		-0.010 ***	0.015 ***	0.008 ***	0.017 ***
Region 3		-0.011	-0.081 ***	0.023 ***	0.035 ***
Region 4		-0.007 ***	-0.036 ***	0.013 ***	0.031 ***
Region 5		-0.005 **	-0.070 ***	0.029 ***	0.027 ***
Metropolitan residence		0.053 ***	-0.216 ***	-0.108 ***	-0.048 ***
Urban residence		0.044 ***	-0.215 ***	-0.047 ***	-0.018 ***
Head of household		0.011 ***	0.013 ***	0.006 ***	0.011 ***
Children 0-14 years in household		0.004 ***	-0.024 ***	-0.000 ***	0.001 *
Has a spouse who works		-0.055 ***	0.155 ***	0.013 ***	0.005 ***
Observations	208,400	208,400	208,400	208,400	208,400

Table 1.4a. First-stage regression results, 1988 and 1995 employment multinomial logit: marginal effects (cont.)

	Manufacturing		Non-tradable sector		
	Informal	Formal	Informal	Formal	Employer (all industries)
			1995		
Column	5	6	7	8	9
Probability (at mean)	0.015	0.061	0.103	0.190	0.027
Male	0.015 ***	0.060 ***	-0.040 ***	0.049 ***	0.036 ***
Experience	-0.000 ***	0.007 ***	-0.004 ***	0.021 ***	0.005 ***
Experience squared	0.000 ***	-0.000 ***	0.000 ***	-0.000 ***	-0.000 ***
White	-0.001 ***	0.002 **	-0.022 ***	-0.028 ***	0.014 ***
Yellow	-0.008	-0.016 **	-0.041 ***	-0.132 ***	0.038 ***
1-3 years education	-0.002	0.018 ***	-0.003 ***	0.052 ***	0.010 ***
4 years education	-0.000 ***	0.034 ***	-0.017 ***	0.092 ***	0.024 ***
5-7 years education	-0.000 ***	0.042 ***	-0.021	0.115 ***	0.028 ***
Completed primary	-0.003	0.046 ***	-0.049 ***	0.170 ***	0.038 ***
9-10 years education	-0.006	0.046 ***	-0.045 ***	0.206 ***	0.048 ***
Completed high school	-0.007	0.054 ***	-0.052 ***	0.293 ***	0.058 ***
12-14 years education	-0.010	0.047 ***	-0.045	0.321 ***	0.067 ***
Completed university	-0.010	0.058 ***	-0.049 ***	0.358 ***	0.075 ***
Region 2	-0.005 ***	-0.007	0.005 ***	-0.000 **	-0.002
Region 3	-0.004	0.053 ***	0.002 ***	0.042 ***	-0.000 **
Region 4	-0.004	0.061 ***	-0.003 ***	0.042 ***	0.003 ***
Region 5	-0.003 ***	-0.021 ***	0.019 ***	0.028 ***	0.003 *
Metropolitan residence	0.002	0.048 ***	0.073 ***	0.185 ***	-0.015 ***
Urban residence	0.002 ***	0.032 ***	0.076 ***	0.139 ***	-0.010 ***
Head of household	0.003 ***	0.046 ***	0.039 ***	0.103 ***	0.021 ***
Children 0-14 years in household	-0.001 ***	-0.002 ***	-0.006 ***	-0.028 ***	-0.004 ***
Has a spouse who works	0.005 ***	0.019 ***	0.021 ***	0.077 ***	0.021 ***
Observations	208,400	208,400	208,400	208,400	208,400

Notes: Marginal effects reported. White and yellow are race indicators (black is omitted category). 0 years of education is omitted education category. Columns headed 0-9 indicate multinomial logit results for each employment classification.

Table 1.4b: First stage regression results, 1988 and 1995 (employment multinomial logit: industry participation constant)

Industry	1987	1988	1989	1990	1992	1993
Unemployed	-4.428	-3.787	-4.476	-4.234	-2.984	-2.783
	(0.134)***	(0.124)***	(0.142)***	(0.130)***	(0.092)***	(0.092)***
Self-employed	-1.157	-1.177	-1.052	-1.168	-1.427	-1.523
	(0.060)***	(0.060)***	(0.060)***	(0.059)***	(0.057)***	(0.057)***
Informal agriculture	-1.374	-1.973	-1.39	-1.483	-2.161	-2.253
	(0.117)***	(0.128)***	(0.125)***	(0.120)***	(0.128)***	(0.125)***
Formal agriculture	-4.487	-5.104	-4.55	-4.358	-5.934	-6.382
	(0.240)***	(0.276)***	(0.284)***	(0.236)***	(0.311)***	(0.314)***
Informal manufacturing	-3.161	-3.059	-3.054	-2.944	-3.73	-3.433
	(0.141)***	(0.140)***	(0.133)***	(0.139)***	(0.145)***	(0.135)***
Formal manufacturing	-4.395	-4.462	-4.116	-4.136	-5.138	-5.153
	(0.091)***	(0.092)***	(0.090)***	(0.091)***	(0.101)***	(0.101)***
Informal nontradable	-1.369	-1.578	-1.456	-1.44	-1.324	-1.206
	(0.064)***	(0.065)***	(0.065)***	(0.063)***	(0.066)***	(0.062)***
Formal nontradable	-3.123	-2.967	-2.841	-2.919	-3.62	-3.575
	(0.064)***	(0.063)***	(0.063)***	(0.063)***	(0.062)***	(0.062)***
Employer	-7.571	-8.099	-6.581	-6.615	-7.724	-8.007
	(0.149)***	(0.156)***	(0.128)***	(0.122)***	(0.139)***	(0.145)***
Observations	177,399	177,376	179,938	184,724	193,931	197,658

Table 1.4b: First stage regression results, 1988 and 1995 (employment multinomial logit: industry participation constant) (cont.)

Industry	1995	1996	1997	1998	1999
Unemployed	-2.978	-3.106	-2.802	-2.659	-2.572
	(0.091)***	(0.087)***	(0.080)***	(0.077)***	(0.072)***
Self-employed	-1.75	-2.158	-2.106	-2.135	-2.054
	(0.055)***	(0.055)***	(0.054)***	(0.054)***	(0.053)***
Informal agriculture	-2.648	-3.175	-2.949	-2.631	-2.73
	(0.129)***	(0.135)***	(0.128)***	(0.129)***	(0.129)***
Formal agriculture	-5.984	-6.483	-7.11	-6.019	-6.919
	(0.291)***	(0.310)***	(0.417)***	(0.294)***	(0.388)***
Informal manufacturing	-3.614	-4.07	-4.038	-4.096	-4.408
	(0.138)***	(0.141)***	(0.133)***	(0.140)***	(0.141)***
Formal manufacturing	-5.394	-5.524	-5.273	-5.474	-5.302
	(0.102)***	(0.101)***	(0.097)***	(0.102)***	(0.103)***
Informal nontradable	-1.558	-1.753	-1.744	-1.636	-1.791
	(0.062)***	(0.060)***	(0.059)***	(0.058)***	(0.058)***
Formal nontradable	-3.802	-3.727	-3.797	-3.802	-3.814
	(0.061)***	(0.058)***	(0.058)***	(0.059)***	(0.058)***
Employer	-7.83	-8.185	-8.477	-8.365	-8.205
	(0.136)***	(0.144)***	(0.137)***	(0.138)***	(0.135)***
Observations	208,400	209,264	219,710	221,088	227,369

Notes: Robust standard errors in parentheses.
* significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.
Non-economically active is omitted category.

Eight different specifications are presented in Table 1.5. While ERPs are insignificant when differences are entered contemporaneously, they become robustly statistically significant in first lags (specifications 4 – 8). The coefficients on lagged ERPs have the expected positive sign and are statistically significant at the usual levels, suggesting that larger declines in protection were associated with larger declines in the industry wage premium over this period in Brazil.[30] Nevertheless, the estimated size of the impact is small: using the ERP coefficient from specification 8, the fall in average ERP from 51.4 percent in 1988 to 20.0 percent in 1995 (with all other variables held at their mean values) would result in a 1.6 percent decrease in average industry wage premium.

Although theory suggests that the pass-through of tariffs to product prices, and thus to wages, is mediated by the sector's import penetration (see Gonzaga *et al.* 2006), import-penetration does not appear to be important in mediating the effect of tariffs on industry-specific wage premiums, as shown by the insignificant coefficients on the interaction terms. The same is not true of (import-weighted) exchange rate effects, which have the predicted (negative) sign[31] when interacted with lagged import penetration: as the currency appreciates and imports become more competitive for a particular industry, wage premiums in that industry decline. When the RER is export-

[30] Although Pavcnik *et al.* (2004:321) expected these results ("The models predict a positive association between industry tariffs and wages, so that declines in industry tariffs lead to proportional declines in industry wages", they did not find them. This may have been due to their use of the less representative PME data, or to specifications that did not include lagged ERPs. Lagging ERPs accounts for the fact that the effects of reduced protection on industry premiums may take time to flow through. Our protection results are, however, consistent with those for Colombia (Attanasio, Goldberg and Pavcnik, 2004), and Mexico (Revenga, 1997).

[31] An increase in our exchange rates means an appreciation in the currency.

Table 1.5 Industry wage premiums and trade exposure

Dependent variable is industry wage premium	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ERP	0.0005	0.0005	0.0005					
	(0.0005)	(0.0006)	(0.0006)					
ERP * lagged import penetration		-0.0001	-0.0005					
		(0.0019)	(0.0019)					
Lagged ERP				0.0003	0.0003	0.0005	0.0003	0.0005
				(0.0001)*	(0.0001)**	(0.0002)***	(0.0001)**	(0.0002)***
Lagged ERP * lagged import penetration						-0.0015		-0.0015
						(0.0011)		(0.0012)
Lagged import penetration		-0.1531	0.0992		-0.1196	-0.0926	0.1245	0.1508
		(0.1533)	(0.1757)		(0.1452)	(0.1505)	(0.1645)	(0.1746)
Lagged export share		-0.0524	-0.1251		-0.0284	-0.0282	-0.1008	-0.1008
		(0.1313)	(0.1354)		(0.1298)	(0.1306)	(0.1334)	(0.1341)
Lagged import penetration * lagged import-weighted RER			-0.001				-0.001	-0.001
			(0.0004)***				(0.0004)***	(0.0004)***
Lagged export share * lagged export-weighted RER			0.0001				0.0001	0.0001
			(0.0000)**				(0.0000)**	(0.0000)**
Observations	210	207	207	210	207	207	207	207
R-squared	0.01	0.01	0.03	0.01	0.02	0.02	0.03	0.04

Notes: Robust standard errors in parentheses.
* significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.

weighted and interacted with lagged export-share, the effect is positive and significant.[32]

Table 1.6 presents the second-stage results for the regression of industry-specific skill premiums on the same set of trade-related variables. For industry-specific skill premiums, once the economy-wide returns to skill are controlled for in the first stage, there are no particular theoretical predictions, and we find that the coefficients on ERPs are insignificant across all specifications. Interestingly, however, we find a fairly robust pattern of negative and significant coefficients on lagged import penetration, suggesting that skill premiums were falling for those industries where the growth in import penetration was largest. We know that these were largely skill-intensive industries that were most highly protected prior to 1988, as seen in Table 1.1. This movement in industry-specific skill premiums is therefore consistent with the decline in the economy-wide skill premium which was documented in Gonzaga *et al.* (2006), and which we also observe. Controlling for the growth in import penetration, there appears to be some evidence that a stronger currency increases the skill premium.[33]

Table 1.7 reports the second-stage results for the regression of industry participation constants from the employment multinomial logit model on the same set of trade-related variables. These results are somewhat harder to interpret, since the ten occupational categories used in the estimation are much more aggregated than the 22

[32] This likely reflects the fact that an increase in an industry's export share would be expected to increase that industry's wage premium.

[33] This may be evidence of quality upgrading in the face of increased import competition.

industries used in the previous two tables, and are basically at the agriculture, manufacturing and services level.[34] Partly as a result, there is a counterintuitive negative sign on lagged ERPs, which suggests a (conditional) movement *towards* the industries experiencing the greater declines in protection. This result is explained by a movement towards the tradable sectors (particularly agriculture) of the reference category of workers in the employment model. Once we look at the unconditional pattern of employment changes for all workers at the disaggregated industry level, in Figure 1.5, we observe the expected positive correlation: employment levels seem to have fallen by more in industries experiencing larger declines in protection.

The only other statistically significant result in Table 1.7 is easier to interpret: lagged export shares are positively correlated with conditional increases in employment, suggesting that industries that succeeded in increasing their exports suffered smaller declines in employment than others.

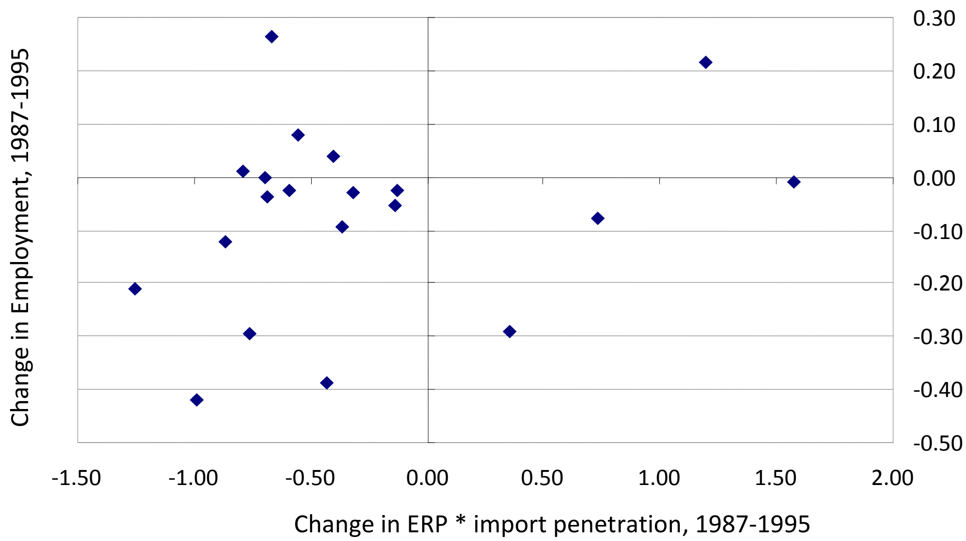
[34] Both formal and informal agriculture categories are regressed on trade variables for the agricultural industry. Formal and informal manufacturing use manufacturing trade variables averaged over the various manufacturing industries, using lagged imports as weights. Formal and informal nontradable, employers and the self-employed categories are assigned zero ERPs, import penetration and export share, but use economy-wide import- and export-weighted real exchange rates.

Table 1.6 Industry skill premiums and trade exposure

Dependent variable is industry skill premium	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ERP	-0.0004	0	0					
	(0.0005)	(0.0007)	(0.0007)					
ERP * lagged import penetration		-0.0031	-0.0027					
		(0.0028)	(0.0027)					
Lagged ERP				-0.0003	-0.0004	-0.0004	-0.0003	-0.0004
				(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Lagged ERP * lagged import penetration						-0.0001		0.0002
						(0.0012)		(0.0014)
Lagged import penetration		-0.2762	-0.486		-0.3476	-0.3453	-0.3578	-0.361
		(0.1652)*	(0.1855)***		(0.1509)**	(0.1551)**	(0.1886)*	(0.1928)*
Lagged export share		0.0746	0.1151		0.0445	0.0446	0.0826	0.0826
		(0.1493)	(0.1577)		(0.1510)	(0.1514)	(0.1591)	(0.1595)
Lagged import penetration * lagged import-weighted RER			0.001				0.0012	0.0012
			(0.0005)*				(0.0005)**	(0.0005)**
Lagged export share * lagged export-weighted RER			0				0.0001	0.0001
			(0.0001)				(0.0001)	(0.0001)
Observations	204	201	201	208	201	201	204	204
R-squared	0.00	0.01	0.02	0.01	0.02	0.02	0.02	0.02

Notes: See Table 1.5

Fig. 1.5. Changes in employment versus change in ERP * import penetration by industry, 1987-95



Source: Authors' calculations. Rates of protection from Kume *et al.* (2000) in de Paiva Abreu (2004); import penetration from Muendler (2003); employment from PNA

Taken together, these results paint a mixed picture. The signs and significance are broadly – if not wholly – consistent with theoretical expectations from models that feature barriers to labor movement across sectors. Larger falls in protection and an exchange rate that makes imports more competitive domestically imply lower industry wage premiums. More exports in an industry are associated with increased wage premiums and employment. Greater import penetration is associated with falls in wage premiums which are greater for more skilled workers (who work mostly in industries that suffered the largest increase in penetration). These results are perhaps more in line with theory and with other accounts of trade liberalization in Brazil than previous attempts at estimating these relationships in Brazil, notably by Pavcnik *et al.* (2004).

Yet, they leave much to be desired. Empirically, the R^2 of each second stage regression is never higher than 0.12. For the wage equations, they are never higher than 0.04, suggesting that, however economically important the joint variation in the trade variables may be, it accounts for a small share of the observed variation in wage premiums across industries and over time. Conceptually, these wage regressions focus on only one of the five mechanisms through which trade reforms are thought to influence changes in wages in developing countries (which were reviewed in Section 1.2), namely changes in industry specific wage and skill premiums.

However, if workers can move across industries over the medium-run, and if market imperfections in labor and product markets are not particularly severe, then it is likely that the main effects of the changes in protection observed in Brazil over this period manifest themselves through (i) worker reallocation across industries and (ii) changes in

Table 1.7. Industry Participation and Trade Exposure

Dependent variable is industry participation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ERP	0.0087	-0.0025	-0.0043					
	(0.0076)	(0.0213)	(0.0229)					
ERP * lagged import penetration		0.0849	0.0965					
		(0.1407)	(0.1574)					
Lagged ERP				-0.0148	-0.0139	-0.015	-0.015	-0.0161
				(0.0041)***	(0.0045)***	(0.0047)***	(0.0069)**	(0.0077)**
Lagged ERP * lagged import penetration						0.0437		0.0483
						(0.0326)		(0.0723)
Lagged import penetration		-1.5541	-0.2417		(1.3357)	(1.2278)	0.4760	1.2010
		(3.9782)	(5.7256)		(1.4342)	(1.5567)	(3.8118)	(4.6518)
Lagged export share		5.9193	4.9226		3.328	4.0074	2.5479	2.9954
		(2.0965)***	(3.4338)		(1.1175)***	(1.0568)***	(2.3503)	(2.3160)
Lagged import penetration * lagged import-weighted RER			-0.0091				-0.0049	-0.0024
			(0.0152)				(0.0105)	(0.0080)
Lagged export share * lagged export-weighted RER			0.0053				-0.0014	0.005
			(0.0183)				(0.0152)	(0.0223)
Observations	80	72	36	72	72	72	36	36
R-squared	0.02	0.02	0.05	0.05	0.06	0.06	0.11	0.12

the economy-wide skill premium. This prediction would accord with the Stolper-Samuelson theorem, but might also be consistent with economy-wide trade-induced SBTC or quality ladder models. In the next section, we turn to the full decomposition of wage changes in Brazil between 1988-1995, in an effort to place the changes implied by the second stage regressions reported in Tables 5-7 into context – both vis-à-vis other changes that may be associated with trade channels, and vis-à-vis other economic processes that are less likely to be driven by trade reforms.

1.5 Decomposition Results

1.5.1 The Distribution of Hourly Wages

Table 1.8 summarizes the results of the decomposition described in Section 1.3.2. It presents four measures of inequality for the 1988 and 1995 hourly wage distributions in Brazil, as well as for the six intermediate counterfactual distributions previously described. The measures are the $90^{th}/10^{th}$ percentile ratio; the mean log deviation (also known as GE(0), or Theil-L index); the Theil-T index (or GE-1) and the Gini coefficient. Figures 1.6-1.11 plot the observed wage growth incidence curve (WGIC) between 1988 and 1995, as well as different counterfactual WGICs, each corresponding to one of the counterfactual distributions listed on Table 1.8. The figures provide a full-distribution, disaggregated decomposition of wage changes.

Table 1.8. Actual and counterfactual hourly wage distributions

	P_{90}/P_{10}	GE(0)	GE(1)	Gini
$\ln w_{ij}^{88} = X_{ij}^{88}\beta^{88} + I_{ij}^{88} * wp_j^{88} + (I_{ij}^{88} * S_{ij}^{88})sp_j^{88} + F_{88}^{-1}(\theta_{i88})$	16.9	0.703	0.780	0.611
$\ln w_{ij}^{1} = X_{ij}^{88}\beta^{88} + I_{ij}^{88} * wp_j^{s} + (I_{ij}^{88} * S_{ij}^{88})sp_j^{88} + F_{88}^{-1}(\theta_{i88})$	16.9	0.705	0.784	0.611
$\ln w_{ij}^{2} = X_{ij}^{88}\beta^{88} + I_{ij}^{88} * wp_j^{s} + (I_{ij}^{88} * S_{ij}^{88})sp_j^{s} + F_{88}^{-1}(\theta_{i88})$	16.7	0.699	0.774	0.609
$\ln w_{ij}^{3} = X_{ij}^{88}\beta^{88} + I_{ij}^{s} * wp_j^{s} + (I_{ij}^{s} * S_{ij}^{88})sp_j^{s} + F_{88}^{-1}(\theta_{i88})$	14.6	0.653	0.731	0.593
$\ln w_{ij}^{4} = X_{ij}^{88}\beta^{s} + I_{ij}^{s} * wp_j^{95} + (I_{ij}^{s} * S_{ij}^{88})sp_j^{95} + F_{88}^{-1}(\theta_{i88})$	12.9	0.600	0.669	0.572
$\ln w_{ij}^{5} = X_{ij}^{88}\beta^{95} + I_{ij}^{s} * wp_j^{95} + (I_{ij}^{s} * S_{ij}^{88})sp_j^{95} + F_{88}^{-1}(\theta_{i88})$	12.3	0.581	0.657	0.566
$\ln w_{ij}^{6} = X_{ij}^{88}\beta^{95} + I_{ij}^{s} * wp_j^{95} + (I_{ij}^{s} * S_{ij}^{88})sp_j^{95} + F_{95}^{-1}(\theta_{i88})$	12.0	0.587	0.691	0.571
$\ln w_{ij}^{95} = X_{ij}^{95}\beta^{95} + I_{ij}^{95} * wp_j^{95} + (I_{ij}^{95} * S_{ij}^{95})sp_j^{95} + F_{95}^{-1}(\theta_{i95})$	12.4	0.617	0.715	0.582

Source: Authors' calculations from PNADs.

The differences between $G(w^1)$ and $G(w^{88})$, which correspond to the impact of the trade-mandated changes in industry-wage premiums, are economically insignificant: counterfactual inequality measures hardly move, and the counterfactual WGIC in Figure 1.6 remains very close to the x-axis. Despite statistically significant coefficients on the tariffs in the second-stage estimation described in the previous section, it appears that changes in the wage distribution due to industry wage premiums between 1988 and 1995 were immaterial. The same is true of changes in industry-specific skill-premiums, which are incorporated into $G(w^2)$, in Figure 1.7. Thus, although our second-stage regression coefficients are statistically significant (while theirs are not), we reach the same essential conclusion on the economics of these impacts as Pavcnik *et al.* (2004): trade liberalization did not affect the Brazilian wage distribution *through industry specific premiums.*

But when relative prices and wages change, firms and industries contract and expand in response. Workers flow across sectors and industries, and their movement is highly selective (on observed and unobserved characteristics). The difference between *G*(w^2) and *G*(w^3) is meant to capture those occupational (employment) changes which took place in response to changes in trade-related variables (as predicted by the second-stage regressions). These counterfactual changes are much larger than those associated with industry-specific wage and skill-premiums. All four inequality measures for *G*(w^3) move closer to their 1995 values: the difference in inequality between this simulation and 1988 ranges between 51 percent of the 1995-1988 difference (for p90/p10) and 76 percent (for the Theil –T). Figure 1.8 reveals that the bulk of the underestimate is due to the bottom of the distribution: whereas *G*(w^3) generates a remarkably good prediction of changes in the wage distribution from the 20th percentile upwards, it considerably underestimates gains for the bottom quintile.

Allowing for changes in the economy-wide returns to education (and thus in a flexible version of the economy-wide skill premium) contributes to a further reduction in inequality, which now in fact overshoots the 1995 targets (for three of the four measures).[35] Consistent with the decline in returns to higher levels of schooling, this simulation does not affect the bottom of the distribution much, but lowers counterfactual incomes in the middle and at the top (Figure 1.9).

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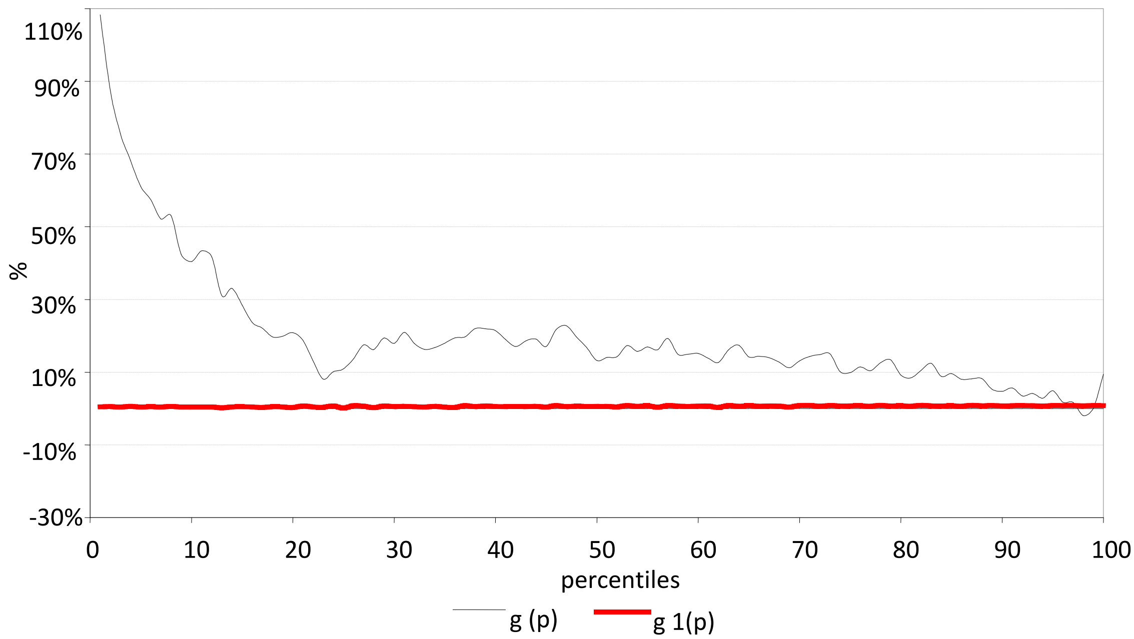
[35] This result is reminiscent of the Gonzaga *et al.* (2006) finding that trade-mandated changes in the (economy-wide) skill premium were larger than those actually observed.

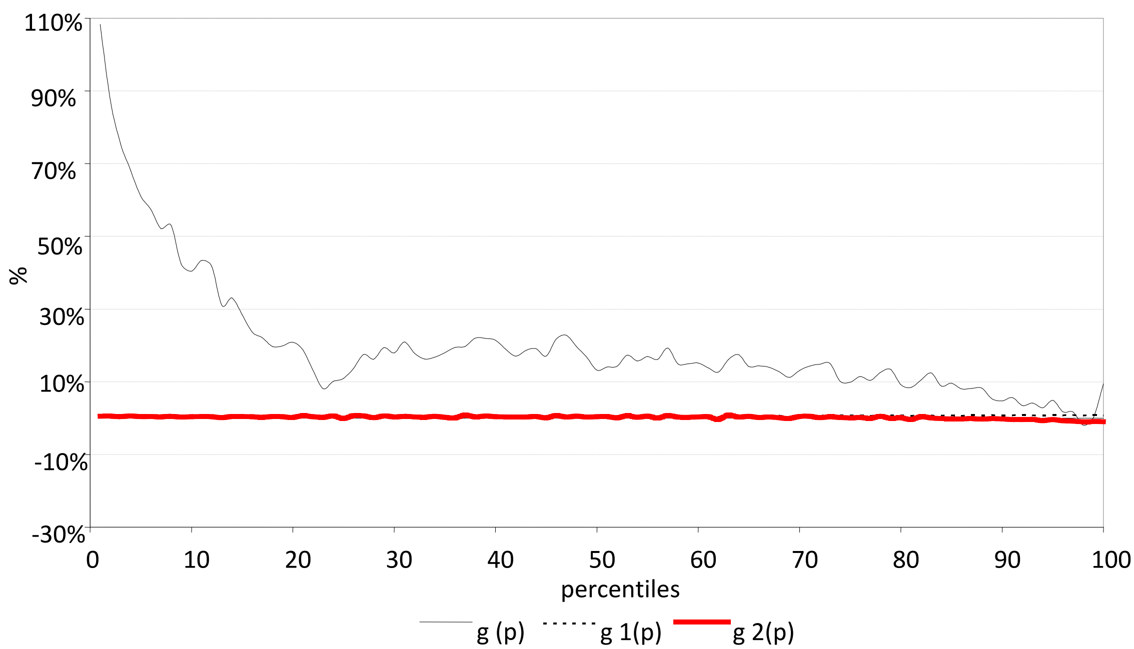
It is harder to attribute these changes to trade reforms, since this counterfactual imports *observed* 1995 coefficients (on education, as well as on industry dummies and industry skill premiums), rather than those mandated by the second-stage. The bulk of the difference between $G(w^3)$ and $G(w^4)$ is due to β_{ed}^{95} which, by its very nature as an economy-wide vector of returns, does not vary by industry and cannot be estimated in a second stage. But the fact that it cannot be included in a Pavcnik *et al.*-style second stage does not mean that it does not reflect trade changes. In fact, as discussed above, if output and labor markets are reasonably well-functioning, a number of theories of trade would predict an important effect of trade liberalization on this coefficient. The Stolper-Samuelson effect would predict a decline in the economy-wide skill premium, and thus an inequality-reduction from importing β_{ed}^{95}. Trade-induced SBTC, as well as most versions of the outsourcing or quality ladder stories would imply an increase in the demand for skilled workers, and thus an increase in inequality from β_{ed}^{95}.

Fig. 1.6 Observed and counterfactual wage growth incidence curves, 1988-1995, industry wage premiums



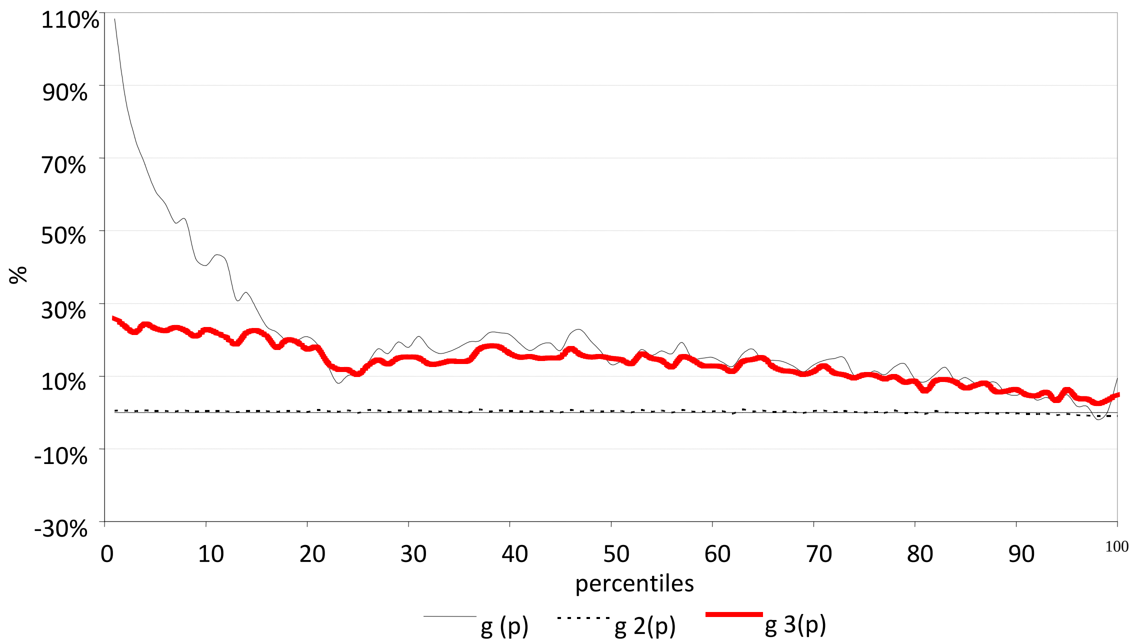
Source: Authors' calculations from PNADs.

Fig. 1.7 Observed and counterfactual wage growth incidence curves, 1988-1995, industry wage and skill premiums



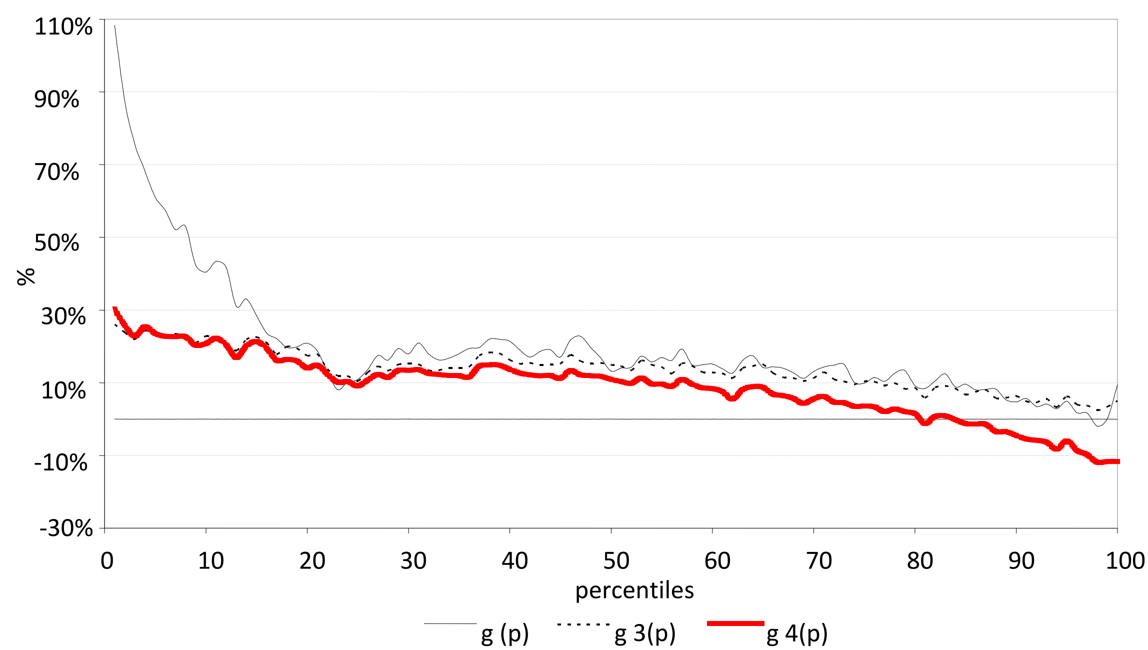
Source: Authors' calculations from PNADs.

Fig. 1.8 Observed and counterfactual wage growth incidence curves, 1988-1995, all trade-mandated changes from second stage



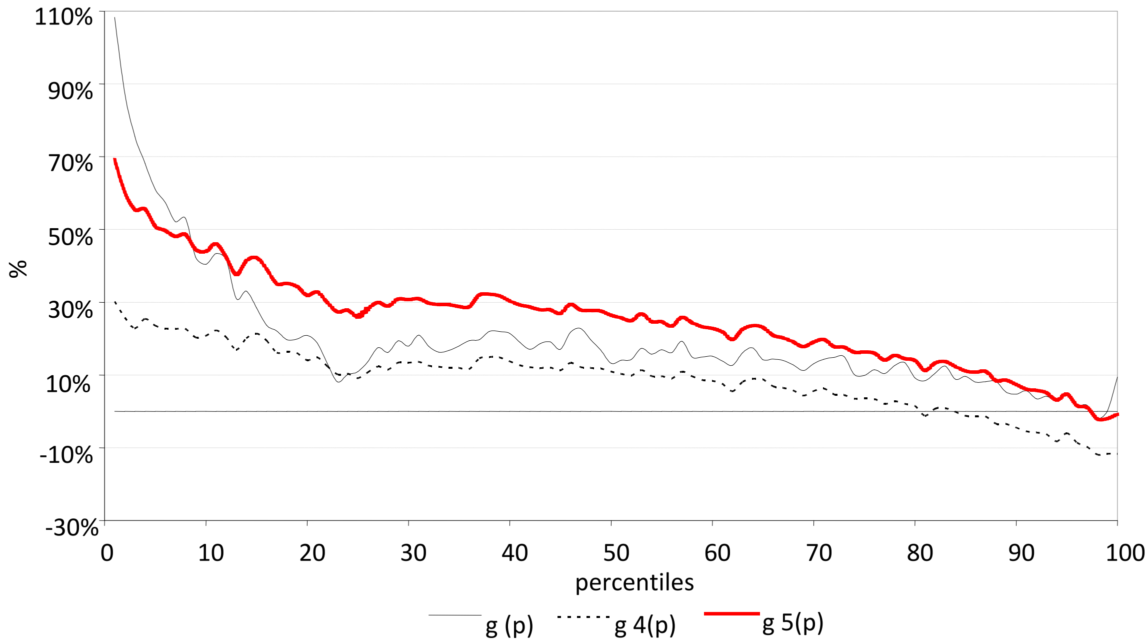
Source: Authors' calculations from PNADs.

Fig. 1.9 Observed and counterfactual wage growth incidence curves, 1988-1995, upper bound on trade effects



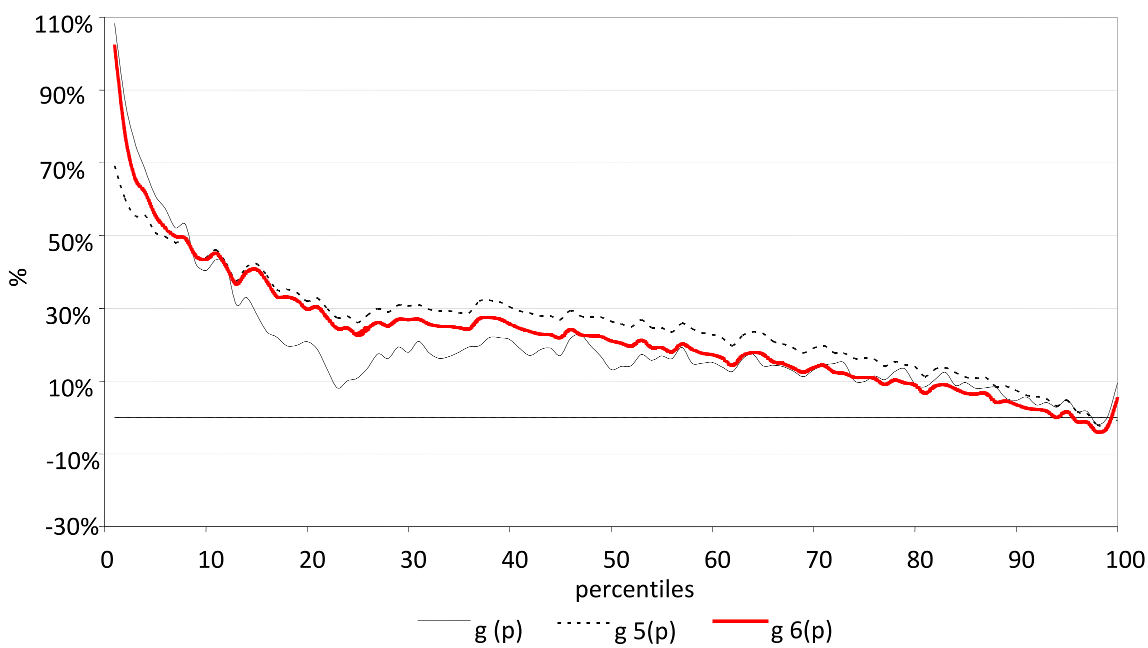
Source: Authors' calculations from PNADs.

Fig. 1.10 Observed and counterfactual wage growth incidence curves, 1988-1995, trade effects and other price changes



Source: Authors' calculations from PNADs.

Fig. 1.11 Observed and counterfactual wage growth incidence curves, 1988-1995, trade effects, other price changes, and changes in residuals



Source: Authors' calculations from PNADs.

On the other hand, changes in β_{ed}^{95} clearly also reflect other economic and demographic changes, notably changes in the supply of skilled workers. As shown in Figure 1.4, there was indeed some growth in the skills of the Brazilian labor force over this period, with the share of skilled workers rising from 20 percent to 24 percent. All in all, this decomposition method does not allow us to separate these changes in inequality into components due to each of the alternative trade hypotheses, and a component due to changes in the supply of skills (or to technology changes unrelated to trade). All that can be said is that the net effect suggests that the Stolper-Samuelson channel and the effects of increased skill supply (which go in the same direction) seem to have outweighed any effects of SBTC or quality compositional changes that might have occurred as a result of trade liberalization.

The two final steps in the decomposition incorporate changes in the remainder of the earnings regression coefficients (the other elements of β) to generate $G(w^5)$, and a rank-preserving transformation in the distribution of residuals to generate $G(w^6)$. Finally, the differences between $G(w^6)$ and $G(w^{95})$ are residually due to changes in the joint distribution of observed characteristics (and in their correlation with the unobserved, including selection). Although effects of trade on the returns to experience, or to unobserved skills, cannot be ruled out, these are not channels on which the literature has focused. Accordingly, we interpret these remaining changes as those which are not attributable to trade effects. Changes in non-education returns are mildly equalizing, and poverty-reducing. Changes in the distribution of residuals contribute to lower incomes in the middle of the distribution and higher incomes at the very top. The net effect is mildly inequality increasing (except for p90/p10). The effect of changes in the distribution of observed characteristics further lowers incomes in the middle of the distribution and raises them above the 75th percentile.

1.5.2. The Distribution of Household Income per Capita

Once the six counterfactual wage distributions $G(w^1)$ to $G(w^6)$ have been simulated, it is a simple matter to create the corresponding counterfactual distributions of household income per capita. Household identifiers link each worker in our data set to a particular household, and information is available on all of its other sources of income (subject to the usual misreporting and measurement issues in an income survey like the PNAD). It is therefore possible to simulate the impact of these counterfactual changes in wages on the distribution of household incomes, and on the inequality and poverty levels associated with it. These results are reported on Table 1.9, and in Figures 1.12-1.17, for the same inequality indices used so far and for the three standard FGT poverty measures. We adopt a relative poverty line of R$87.55 in 2004 prices, which corresponds to 50 percent of the 1988 median household per capita income.

Before discussing these results, it is important to recognize that their limitations are even greater than those for the wage distribution decompositions analyzed so far. In addition to the same caveat about path dependence, now the absence of general equilibrium effects extends to any indirect impacts of trade (or any other changes) on family composition, or on the occupational decisions of household members other than spouses. There are also important changes in other, unrelated policy parameters, such as the real value of pension payments and other transfers, which are consigned to the residual – which is therefore larger than in the decomposition described on Table 1.8.

Table 1.9. Actual and counterfactual household per capita income distributions

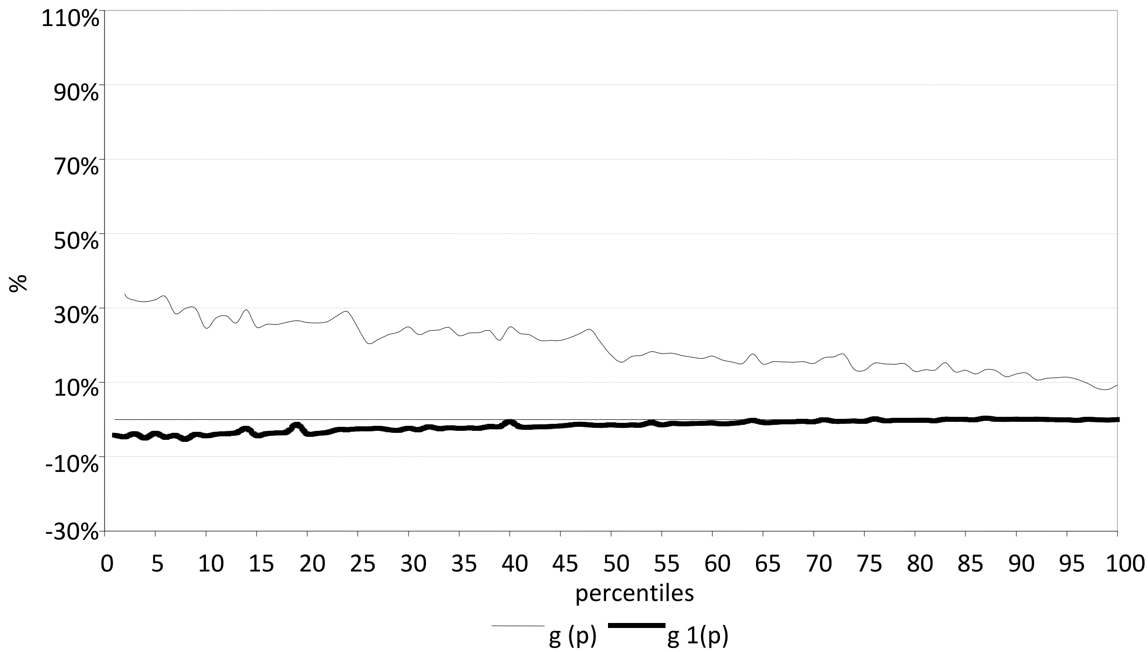
	P_{90}/P_{10}	GE(0)	GE(1)	Gini	Poverty Line R$87.55		
					FGT(0)	FGT(1)	FGT(2)
$HPCI_{ij}^{88}$	19.3	0.717	0.750	0.609	27.7	11.5	6.7
$HPCI_{ij}^{1}$	19.9	0.729	0.760	0.613	27.7	12.1	7.1
$HPCI_{ij}^{2}$	19.7	0.724	0.755	0.611	27.8	12.1	7.1
$HPCI_{ij}^{3}$	16.9	0.658	0.692	0.589	21.2	8.7	4.9
$HPCI_{ij}^{4}$	15.3	0.613	0.644	0.571	21.2	8.6	4.9
$HPCI_{ij}^{5}$	15.4	0.616	0.645	0.572	19.0	7.6	4.3
$HPCI_{ij}^{6}$	15.2	0.621	0.663	0.575	19.7	7.8	4.4
$HPCI_{ij}^{95}$	16.9	0.660	0.706	0.592	23.8	10.5	6.3

Notes: This is a relative poverty line, calculated to represent 50 percent of the median household per capita income in 1988 (expressed in 2004 prices.
Source: Authors' calculations from the PNAD.

As in the hourly wage distribution, trade-mandated changes in industry wage premiums and industry-specific skill premiums have very limited effects (although they are somewhat more inequality increasing, suggesting that the workers hardest-hit by wage declines in contracting industries belonged to poorer households: Figures 1.12 and 1.13). The biggest impact, as before, comes in the transition from the second to the third counterfactual (Figure 1.14). The changes in occupations across the distribution which occur in response to changes in the occupation-specific terms in the multinomial logit model are vastly poverty- and inequality-reducing. They contribute a decline of six points in the headcount index, actually overshooting the observed decline. Inequality measures move very close to the observed 1995 values, and the counterfactual growth incidence curve corresponding to these 'full trade effects' lies quite close to the observed GIC (1995-1988).

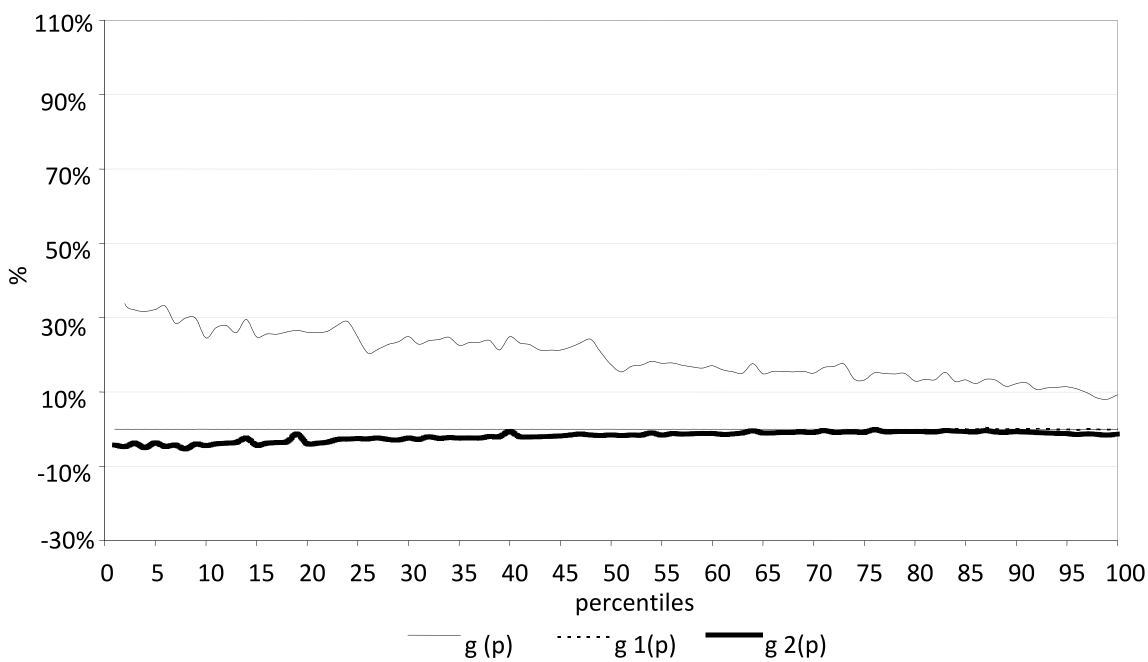
Allowing for changes in the returns to education β_{ed}^{95} in simulation 4 contributes to a further reduction in inequality, as in the wage distribution, and to an under-prediction of all, but particularly the highest, incomes (Figure 1.15). That is partly corrected by allowing the other earnings regression coefficients (including the constant) to take their 1995 values (Figure 1.16). Finally, replacing the earnings regression residuals with a rank preserving transformation of the 1995 residuals leads to column HPCI (6) in Table 1.9, and to the counterfactual GIC in Figure 1.17

Fig. 1.12 Observed and counterfactual household per capita income growth incidence curves, 1988-1995, industry wage premiums



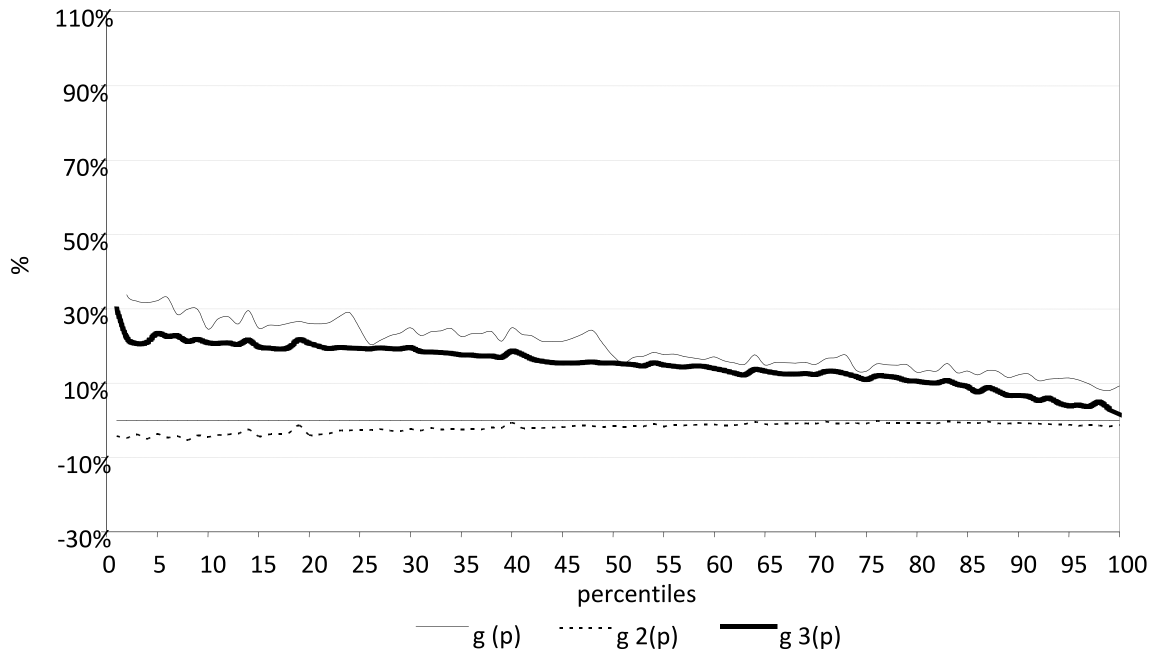
Source: Authors' calculations from PNADs.

Fig. 1.13 Observed and counterfactual household per capita income growth incidence curves, 1988-1995, industry wage and skill premiums



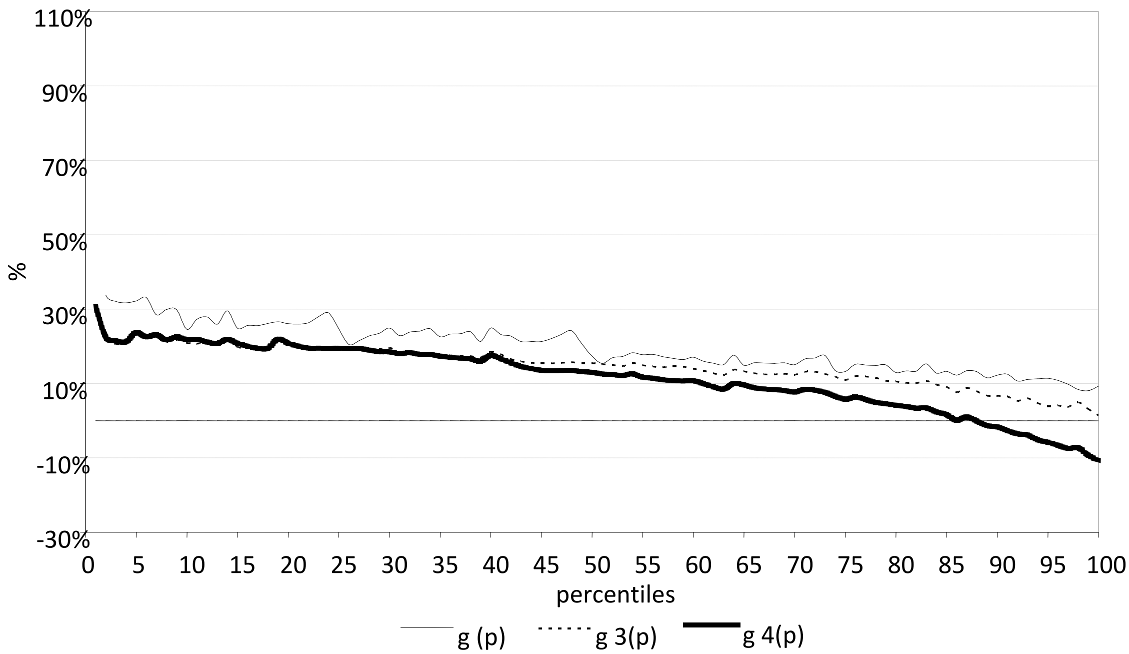
Source: Authors' calculations from PNADs.

Fig. 1.14 Observed and counterfactual household per capita income growth incidence curves, 1988-1995, all trade mandated changes from second stage



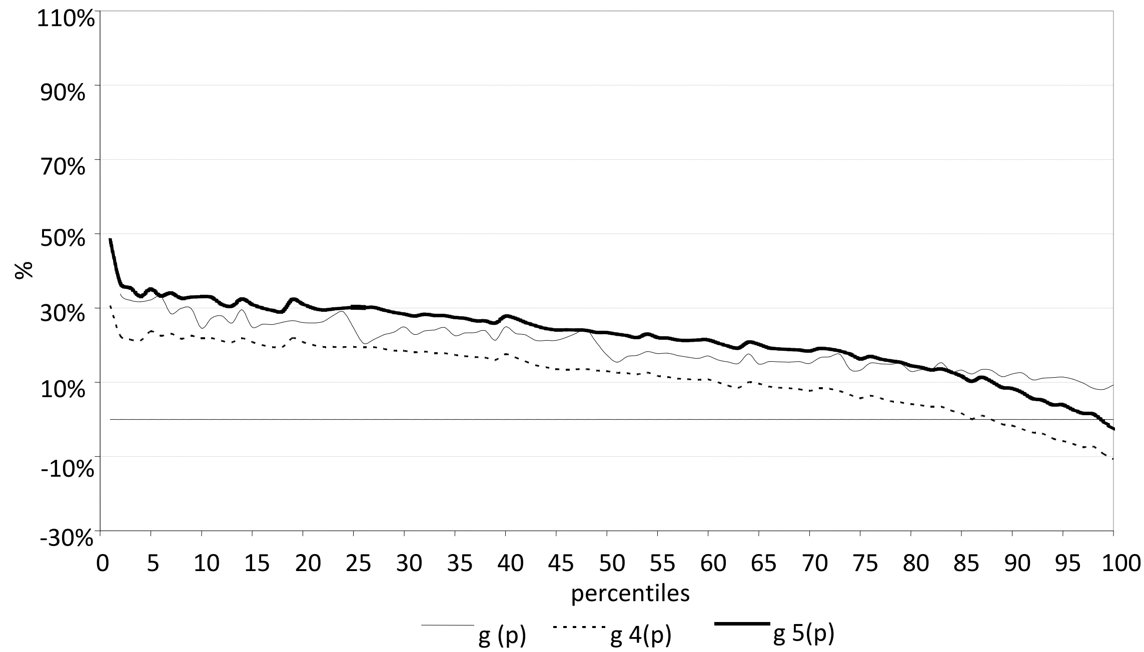
Source: Authors' calculations from PNADs.

Fig. 1.15 Observed and counterfactual household per capita income growth incidence curves, 1988-1995, upper bound on trade effects



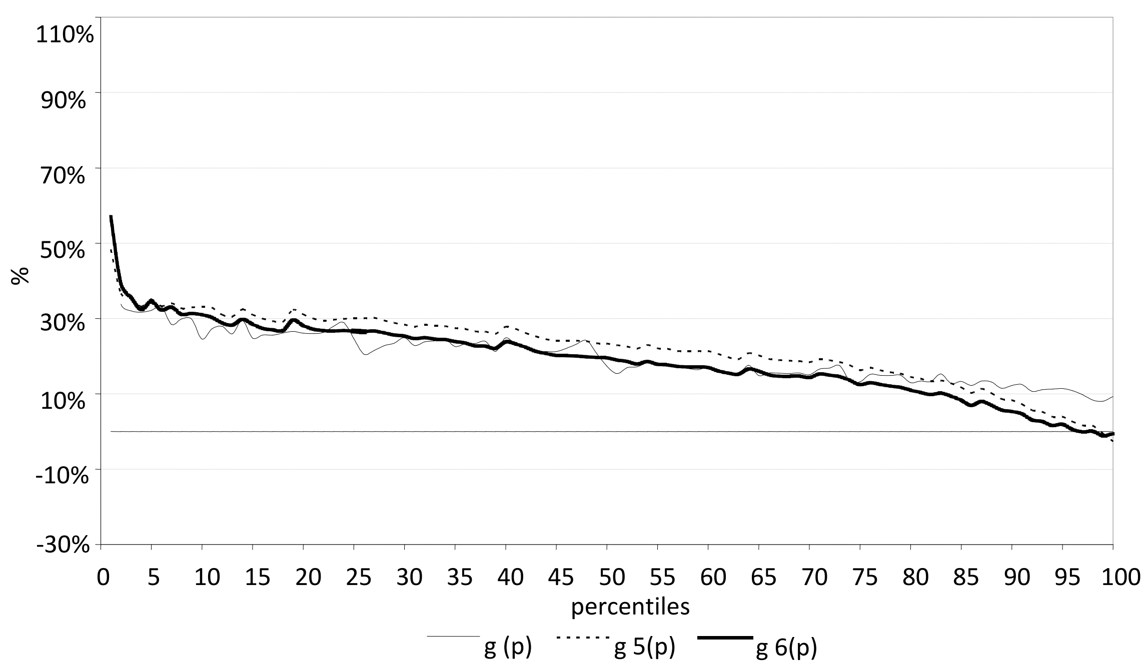
Source: Authors' calculations from PNADs.

Fig. 1.16 Observed and counterfactual household per capita income growth incidence curves, 1988-1995, trade effects and other price changes



Source: Authors' calculations from PNADs.

Fig. 1.17 Observed and counterfactual household per capita income growth incidence curves, 1988-1995, trade effects, price changes, and changes in residuals



Source: Authors' calculations from PNADs.

The underestimates in poverty and inequality implied in this final counterfactual reflect two main factors. First, there were substantial changes in labor force participation and informality over this period which were unrelated to trade and are thus not captured by the simulation. Second, there were also important changes in the incidence of non-labor incomes, with a decline in the real value of minimum-wage linked pensions at the bottom of the distribution, and an increase in the real value of retirement earnings at the top. Both of these trends, which were documented in Ferreira and Barros (1999), help account for the difference between the counterfactual and the actual GICs in Figure 1.17 (and between the two bottom lines of Table 1.9).

These earnings-based simulations are *not* the most suitable way for understanding differences between full household income distributions. The extended version of this approach which is described in Bourguignon *et al.* (2004) would be much more appropriate. The point of this subsection, then, was merely to point out that the links between trade – and, in particular, trade-mandated employment flows across sectors and formality status – and wage inequality do appear to carry through to the changes we have observed in the distribution of HPCY in Brazil over this period, including a substantial part of the observed poverty reduction.

1.6. Conclusions

Using a nationally representative sample of workers in all sectors of the economy, this chapter has sought to quantify the impacts of the 1988-1995 trade liberalization episode on the Brazilian wage distribution. Our results confirm previous findings that changes in industry wage premiums and industry-specific skill premiums did not meaningfully contribute to changes in the distribution of hourly wages. Trade reforms *did* contribute to the observed reduction in inequality, but this happened through other channels. Chief among them were trade-induced changes in employment levels across sectors, industries and formality categories (formal, informal, self-employed, employer). The reallocation of workers that our model predicts to have arisen from changes in levels of protection, exchange rates, import penetration and export shares between 1988 and 1995 accounts for more than half of the observed changes in three out of four measures of inequality in hourly wages.

The other key channel through which trade reform is likely to have affected the distribution of wages is through changes in the economy-wide skill premium. This is the channel on which Gonzaga *et al.* (2006) focused, and they argued that changes in the skill premium mandated by a Stolper-Samuelson model of trade would account for more than the actual change in skill-premium *in manufacturing* during 1988-1995. While our approach is unable to identify changes in the economy-wide skill premium which are due to trade variables from those which are not, our findings are consistent with the

Gonzaga *et al.* results: returns to education fell over the period, contributing to a decline in inequality which did overshoot the observed decline. If there was any skill-biased technical change, or if other forces for greater demand for skill were at work, they were more than offset by the joint force of the Stolper-Samuelson effect of trade liberalization in an economy that used to protect skill-intensive industries, and of increases in the supply of more educated workers.

Overall, even if one does not attribute the decline in the economy-wide returns to education to the trade reforms (despite evidence from other sources that part of it is attributable to the Stolper Samuelson effect), our results suggest that trade liberalization did play an important part in the reduction of wage inequality in Brazil during 1988-1995. The counterfactual wage growth incidence curve that includes the combined wage and employment effects mandated by changes in trade variables accounted for 59 percent of the observed change in the Theil-L index, 61 percent of the change in the Gini coefficient, and 76 percent of the change in the Theil-T index. Among the combined effects, changes in occupation and employment levels across industries were by far the most important. These reductions in wage inequality did appear to extend to declines in household income inequality, and in the poverty rate.

Some of the implications of these findings are as follows. There is no reason why researchers concerned with the distributional effects of trade liberalization should focus exclusively on the manufacturing sector, or only on industry-specific wage premiums.

Indeed, it would seem that employment flows and changes in the occupational structure of the labor force play a central role, and should be considered explicitly. For policy-makers, it would seem that in countries where protection was stronger for industries intensive in skilled workers (which was not the case in Mexico, Chile or Colombia, but was the case in Brazil), there need be no mandatory trade-off between gains in efficiency and productivity on the one hand, and increases in inequality or poverty on the other. Quite the contrary: the same liberalization efforts that lead to productivity gains may also lead to wage gains at the bottom of the distribution, and to reductions in poverty and inequality.

Chapter Two: Large-scale Child Health and Nutrition Interventions: Indonesia's *Posyandu*[36]

2.1. Introduction

Child mortality and morbidity is a key issue in the developing world; of the 10.8 million deaths under five years old which occur annually in the world, 99 percent are in developing countries, with 80 percent concentrated in just twenty of them (Bryce *et al.* 2008). Leading causes are perinatal and neonatal complications, respiratory diseases, diarrheal diseases, malaria and measles (WHO 2003; Black *et al.* 2005a). Malnutrition also plays a key role, estimated as an underlying cause in 35 to 60 percent of cases; that is, children who would not have died from other causes if they had not been malnourished (e.g. Pelletier *et al.* 1995; Bryce *et al.* 2005a; Ashworth *et al.* 2008).

Surviving early childhood health problems may still mean adverse effects in later life. Malnutrition, for example, leads to greater disease susceptibility, higher mortality and

[36] This chapter owes a great debt to many people. Critical data were received from Kathleen Beegle and John Strauss. Esther Duflo graciously made data available. Research in Indonesia was facilitated by the Brighten Institute, and thanks are due to all involved there, in particular Dwi Wahyuniarti, Dicky Firmansyah, Hermanto Siregar and Sonny Priyarsono. Many interviews were conducted in Jakarta and there are far too many individuals to mention, but thanks must be made to Vivi Alatas, Ibu Atmarita, Ibu Aswatini, Pak Fajar, Stephanus Indradjaya, Pak Jarot, Pak Maliki, Pak Minarto, Pak Rachmat, Professor Soekirman, Pak Sugiri, Dr Haryono Suyono, Thee Kian Wee, Pak Trihono, and Bill Wallace. Primary and secondary research was conducted as an IGERT fellow in the Columbia University International Development and Globalization program. The research presented here was developed over regular seminars with this group, and has received invaluable comments and support from Gabriella Carolini, Shubha Chakravarty, Dan Choate, Marissa King, Dan Neilson, Laura Paler, Cuz Potter and Matt Winters. In particular, much is owed to Akbar Noman, Eva Kaplan and Joseph Stiglitz. Support and assistance from the Department of Economics at Columbia University was received in particular from Kiki Pop-Eleches and Doug Almond. The final draft received excellent comments from Claudia Rokx. Funding is gratefully acknowledged from the Initiative for Policy Dialogue (IDG). This chapter is dedicated to Irfan Nasution, without whom it could never have been written.

impaired cognitive development in the short-term, and in the longer-term also results in lower educational attainment, income and wealth (see summaries by Behrman *et al.* 2004; Victora *et al.* 2008; Horton *et al.* 2008). Moreover, disadvantages due to early childhood malnutrition can be transmitted to later generations through decreased birth weight of offspring, the negative effects of which are well-documented (see Currie and Hyson 1999; Almond *et al.* 2005; Black *et al.* 2007).

Child mortality and malnutrition is thus a major focus of development programs. Millennium Development Goal One aims to halve between 1990 and 2015 the proportion of people who from suffer from hunger, and Goal Four aims to reduce the 1990 under-five mortality rate by two-thirds by 2015. However, the latter goal is the furthest from being reached of any (UNICEF 2009). While the efficacy of community-based child health and nutrition program components is well-established (Mason *et al.* 2006), implementing these at scale has proven difficult (e.g. Allen and Gillespie 2001; Gwatkin *et al.* 2004; Bryce *et al.* 2005b; Gillespie *et al.* 2007), impact evaluation in terms of net effects on health outcomes is sorely lacking, and changes in outcomes due to large-scale programs are not well known (Mason *et al.* 2006).

Beyond the immediate concerns of child health, improved nutrition operates through many channels to benefit countries: saving resources currently directed towards diseases and malnutrition; direct gains from improvements in physical stature and improved micronutrient status; indirect gains from links between nutritional status and schooling, nutritional status and cognitive development, and subsequent links between schooling, cognitive ability and adult productivity (Behrman *et al.* 2004). Furthermore, there is significant interest in the effectiveness of various health and education interventions in improving education outcomes (Glewwe and Kremer 2006; Glewwe and Miguel 2008; Orazem and King 2008), and whether such interventions should target people earlier or later in life (Carneiro and Heckman 2003; Krueger 2003).

This paper evaluates Indonesia's *posyandu* program, an inexpensive integrated child primary health care program which was implemented on a national scale in the 1980s and 1990s. Established ultimately in almost every village, the *posyandu* was a community-based health post providing immunization, growth monitoring and nutritional education, oral-rehydration salts, vitamin A supplementation for children and iron supplementation for mothers, and family planning advice. The main research questions I address are how effective the program was in reducing child mortality and malnutrition, whether there were longer-term effects, how cost-effective it was and whether we can determine the role played by its different components.

To my knowledge, this is the first study using household-level data to demonstrate the effectiveness of such a program on a very large scale. I estimate that the *posyandu* reduced under-five mortality by 36 deaths per 1,000 children, which is consistent with the reduction we would expect from the known clinical efficacy of its interventions, and represents 40 percent of the national decrease from 1980-2000. Underweight and stunting were reduced by 19 to 26 percent, with the effect concentrated in children two years and younger. There is also evidence that improved nutritional status led to large increases in test scores (0.24 to 0.37 standard deviations). A comparison of costs per child and cost-effectiveness with similar programs in other countries and other interventions indicates that the *posyandu* program is amongst the most cost-effective child health care interventions ever implemented. Finally, I briefly examine why this large-scale program was successful in Indonesia when there is limited evidence that similar such programs have been effective elsewhere.

Section 2.2 presents an overview of the relevant literature. Section 2.3 summarizes the *posyandu* program while Section 2.4 discusses the data and empirical methodology. The main analytical results appear in Section 2.5, Section 2.6 assesses cost-effectiveness, while Section 2.7 concludes.

2.2. Child Mortality, Malnutrition and Human Capital Development: Causes, Consequences and Interventions

This section begins by reviewing the nature of child mortality and malnutrition, and their causes and consequences. It then looks at the efficacy of interventions before discussing the problems of scaling them up. Finally it briefly reviews two issues in the development of human capital: the merits of health- and education-based interventions, and the merits of early or late interventions.

2.2.1 Child mortality and malnutrition

Just under 11 million children aged under five years die annually. It is estimated that 73 percent of under-five mortality is attributable to six causes: pneumonia (19 percent), diarrhea (18 percent), malaria (8 percent), neonatal sepsis or pneumonia (10 percent), preterm delivery (10 percent) and asphyxia at birth (8 percent) (Bryce *et al.* 2005a).[37]

Moreover, the role of under-nutrition is estimated as an underlying cause in 35 to 60 percent of all cases (Pelletier *et al.* 1995; Pelletier and Frongillo, 2003; Bryce *et al.* 2005a; Ashworth *et al.* 2008), and more specifically, as 61 percent for diarrhea, 57 percent for malaria, 52 percent for pneumonia and 45 percent for measles (Bryce *et al.* 2005a),[38] affecting both disease incidence and severity (Scrimshaw 1968; Chandra 1991, 1997; Tomkins and Watson 1989).

There are a number of dimensions to malnutrition; briefly outlining them places the nutrition component of the *posyandu* into context. First, malnutrition has multiple roots. It can be caused by insufficient food supply, a lack of purchasing power, poor health conditions, poor child care practices, and poor nutritional knowledge. It is important to recognize that the *posyandu* address mainly the last of these, and are not, in themselves, a comprehensive malnutrition intervention. Indeed, “poverty, hunger

[37] While these estimates are based on data with less than global coverage, this is relatively consistent with earlier work (WHO 2003). Deaths from HIV/AIDS, while not yet a leading cause, are growing fast (WHO 2003).

[38] See Caulfield *et al.* (2006) for a summary, and also Caulfield *et al.* (2004a, 2004b).

and malnutrition are linked. Strauss and Thomas (1995, 1998) and Hoddinott, Skoufias and Washburn (2000) document the empirical literature relating dimensions of access and intakes of calories to household consumption levels. A reasonable reading of these studies suggests an income-calorie elasticity of 0.2 to 0.3" (Behrman *et al.* 2004, p1). Second, malnutrition manifests itself as both over- and under-nutrition, with obesity and related health issues becoming an important issue not just in developed countries but in the developing world as well (Martorell 2008). Under-nutrition is the significant issue in Indonesia, however, and it is in this context that the *posyandu* operate. Finally, nutritional deficiency can be macro- or micro-nutrient related. Macro-nutrient malnutrition (PEM, or protein-energy malnutrition) is reflected in children being underweight or underheight. Micro-nutrient deficiency is more likely to manifest itself through illness, disease or developmental impairment. The *posyandu*, with their growth monitoring and nutritional education component as well as vitamin A supplementation, are concerned with both, although the malnutrition indicators used in this paper are oriented towards macro-nutrient deficiency.

Low weight-for-age is the most widely used indicator of malnutrition (Martorell 2008), used by the WHO and UNICEF, and incorporated into the Millennium Development Goals. A child whose weight-for-age z-score is less than -2 standard deviations is considered underweight. However, there is a growing consensus that stunting (height-for-age z-score less than -2 SD) is a better indicator of malnutrition, as it results from chronic malnutrition (Martorell 2008), whereas underweight can reflect short-term malnutrition (Caulfield et al., 2006), and stunting is seen as the best predictor of long-term consequences for human capital (Victora *et al.* 2008). This paper uses both stunting and underweight in the analysis.

Malnutrition has both short- and long-term consequences. The former are summarized in Rogers (2002) and Behrman *et al.* (2004). Besides the susceptibility to disease and higher risk of mortality already discussed, severe malnutrition in early childhood often results in impaired cognitive development (e.g. Pollitt 1990; Granthan-McGregor *et al.* 1999), with poorer cognitive function, poorer motor skills, lower activity levels, less interaction with their environment and a lower rate of skill acquisition (Lasky *et al.* 1981; Johnston *et al.* 1987; Granthan-McGregor *et al.* 1997, 1999). Glewwe and King (2001) conclude that malnutrition which persists into the second year of life is most critical for cognitive development, whereas malnutrition in the first six months has less effect because it can be reversed, and that a one standard deviation reduction in height reduces test scores by one-third of a standard deviation in that score. In addition to macro-nutrient malnutrition, micro-nutrient malnutrition also affects cognitive and motor development, particularly iodine deficiency and anemia (see Karoly *et al.* 1998; Martorell 1999; Lozoff *et al.* 2000; Currie and Thomas 2000; Currie 2001; Alderman *et al.* 2001; Glewwe and King 2001; Glewwe 2002; and Behrman *et al.* 2004). The effect of health interventions in reversing such effects is reviewed in a later section.

Rogers (2002), Horton *et al.* (2008), Martorell (2008) and Victora *et al.* (2008) review the literature on long-term consequences. Recent longitudinal studies provide direct evidence that child malnutrition affects education, wages and incomes.[39] Hoddinott *et al.* (2008) found Guatemalan men receiving supplements before they were three years old had wages 34 to 47 percent higher than the control group and annual incomes 14 to 28 percent higher. In the same study, Maluccio *et al.* (2006) linked the supplement to increased schooling for women by 1.2 years and increased reading comprehension by 17 percent for both sexes. Children exposed to the 1959-61 Chinese famine in their first years of life were associated with a 3cm lower adult height and lower income and wealth (Chen and Zhou 2007). Another long-term study of cohorts in five developing countries found that poor fetal growth and stunting by the age of two was associated with shorter adult height, lower schooling attainment, and reduced income (Victora *et al.* 2008). Moreover, under-nutrition (particularly fetal under-nutrition) can lead to increased probabilities of chronic non-infectious diseases later in life (Rogers 2002; Behrman *et al.* 2004; Victora *et al.* 2008), giving credibility to the Barker hypothesis (Barker 1992, 1994; Schurch and Scrimshaw 1998).[40]

[39] There is also a considerable literature on the links between *current* nutrition, productivity and wages and income; see Rogers (2002) for a summary and discussion. The logical links between nutrition, health status and economic growth (e.g. Ho 1985; Behrman 1993; Fogel 1994; Acemoglu and Johnson 2007) have been more difficult to establish empirically (Rogers 2002).

[40] The 1980s' hypothesis of 'small but healthy' (Seckler 1982; Sukhatme and Margen 1982), which held that malnutrition did not have the health effects thought because the body adapts to low nutritional intakes, lost support in the wake of considerable negative evidence (Viteri and Torun 1981; Widdowson 1985; Messer 1986).

Shorter maternal height due to childhood malnutrition is important because shorter women have more complications during childbirth, have children with lower birth weight, and experience a higher risk of both child and maternal mortality (Kramer 1987; World Bank 1993; WHO 1995; Ramakrishnan *et al.* 1999; Kremer *et al.* 2001). In particular, the association with lower offspring birth weight means malnutrition can have intergenerational effects; children with low birth weight tend to have significantly more health problems, poorer cognitive development, and earn less income later in life (e.g. Currie and Hyson 1999; Almond *et al.* 2005; Almond and Mazumder 2005; Almond 2006; Black *et al.* 2007).

2.2.2 Efficacy of specific interventions

A number of interventions are used by the *posyandu* program to combat child mortality and malnutrition: immunization, oral rehydration therapy, vitamin A supplementation, education on breastfeeding and complementary foods, and growth monitoring. Their field efficacy is considered here.

Immunization against a number of childhood diseases has a high degree of efficacy. Vaccines against the six diseases targeted by the Expanded Programme on Immunization (EPI), and thus the *posyandu*, are particularly effective in reducing mortality due to tuberculosis (75 to 86 percent), diphtheria (87 percent), tetanus (80 to 95 percent), pertussis (70 to 90 percent), polio (72 to 98 percent) and measles (85 to 98 percent) (Brenzel *et al.* 2006). Furthermore, vaccines against diphtheria, pertussis and measles also reduce lower acute respiratory infections, which account for 19 percent of under-five deaths (Simoes *et al.* 2006).

ORT (oral rehydration therapy) was introduced in 1979 and despite its now widespread use against diarrheal diseases, its efficacy in the field has been difficult to establish, primarily because it was introduced simultaneously along with a number of other potentially important interventions, such as promotion of breastfeeding, improved supplemental feeding, greater female schooling, and immunization against measles (Victora *et al.* 2000). At the same time, improvements in socioeconomic status, water and sanitation and the provision of vitamin A may also have played a part. Consequently, ORT's efficacy in reducing diarrheal deaths on a large scale has yet be established conclusively. However, Victora *et al.* summarize the few detailed country case studies available.[41] The four countries examined (Brazil, Philippines, Egypt and Mexico) experienced sustained annual declines in diarrheal deaths of 5 to 16 percent, with ORT coverage between 25 to 60 percent, without comparable declines in other causes of death nor a significant role from the other possible interventions discussed. They conclude that "although these case studies are not appropriate for establishing causality beyond doubt, they are all compatible with a plausible impact of ORT on diarrhoea mortality.[42] With regard to ORT and diarrhoea, trends have certainly been

[41] The global data surveyed by Victora *et al.* show a positive trend in ORT usage and a decline in deaths attributable to diarrhea, but problems with the data quality and the various confounding factors mean a causal relationship is far from established.

[42] Plausible is being used here in the technical sense employed by Habicht *et al.* (1999).

moving in the expected direction over the last 20 years. Use rates have increased and mortality has fallen sharply. Alternative explanations were not found in the few countries where they were sought. There are strong grounds for considering that CDD programs, in particular the promotion of ORT in conjunction with other key interventions, have had a large role in the marked reduction in deaths caused by diarrhoea among children." (p1253).

Vitamin A supplementation has been demonstrated to increase child survival. Estimates from meta-analyses of field trials of mass supplementation range from a 25 to 35 percent reduction in child mortality (Beaton *et al.* 1993; Fawzi *et al.* 1993; Allen and Gillespie 2001).[43] However, this reduction in mortality is not independent of other causes of death; vitamin A deficiency is often concurrent with deaths from diarrheal diseases (being a co-factor in cases ranging from 50 percent (UNICEF 2009) to 61 percent (Bryce *et al.* 2005a) to 71 percent (Beaton *et al.* 1993)) and measles (33 percent (UNICEF 2009), 45 percent (Bryce *et al.* 2005a), 46 percent (Beaton *et al.* 1993)). The health benefits of vitamin A are through reduced mortality only; there is little evidence of an effect from vitamin A supplementation on child growth (Allen and Gillespie 2001; Behrman *et al.* 2004; Bhutta *et al.* 2008).

[43] However, given that "it is also likely that the children missed in any wide-scale program are also likely to have higher than average risk of mortality (and also that the marginal costs of reaching these children are higher than the average costs)", Behrman *et al*. (2004, p26) use a 10 percent reduction as a conservative estimate of the effect of a large-scale vitamin A supplementation program.

That breastfeeding reduces child mortality is well-established (see Bhutta *et al.* 2008 for a summary). It has been estimated that exclusive breastfeeding for infants up to six months reduces mortality in developing countries by three to six times (WHO 2000). However, even with optimum breastfeeding children will become stunted if they do not receive adequate complementary foods after six months (Black *et al.* 2008). Education on complementary feeding during breastfeeding for older infants was associated with a 0.25 increase in height-for-age z-score in food-secure populations (Bhutta *et al.* 2008).

The final component of the *posyandu* is growth monitoring and nutrition education. Despite being in common use for the past 25 years (as part of UNICEF's GOBI approach: growth monitoring, oral rehydration, breastfeeding and immunization), growth monitoring has not been well-evaluated and its efficacy has yet to be properly established. Ashworth *et al.* (2008) summarize the literature in a recent review article, discussing a number of small-scale studies with evidence that children whose growth is monitored and whose mothers receive nutrition and health education and have access to basic child health services have a better nutritional and survival status than those who do not. However, they find little evidence of successful large-scale programs using growth monitoring. Bhutta *et al.* (2008) go so far as to classify growth monitoring as an intervention not recommended for implementation anywhere due to lack of evidence on efficacy, although this is controversial (Martorell 2008). An important point made by both Martorell and Ashworth *et al.* is that growth *monitoring* is a tool, not an intervention. It is a simple and inexpensive procedure that involves the weighing of children and plotting the weights over time, and is intended to be effective as part of a growth *promotion* strategy, which "implies using the information to counsel mothers about best practices in feeding and caring for children" (Martorell 2008, p8). Indeed, Ashworth *et al.* cite some evidence of successful small-scale programs which incorporate both growth monitoring and nutrition education.[44] Similarly, where large-scale programs using growth monitoring have not been found to be effective, they suffered from low coverage and limited counseling (Ashworth *et al.* 2008). In these cases it was the failure of the *promotion* rather than *monitoring* strategies that undermined the program. Thus "[A]t issue is whether the growth monitoring part is needed; can the promotion part be done effectively without the monitoring part? Can growth monitoring be an effective platform for anchoring other child health and nutrition interventions? These questions cannot be answered with certainty and good evaluations of growth monitoring and promotion programs are needed." (Martorell 2008, p8).

With respect to malnutrition, the effectiveness of interventions is not linear over a child's life. A consensus has emerged that there is a 'window of opportunity' for addressing malnutrition and that interventions should focus on babies *in utero* and in their first two years of life, since this is when most growth failure occurs (Allen and Gillespie 2001; World Bank 2006; Martorell 2008; Bryce *et al.* 2008). For example, stunting begins *in utero* and continues until the second or third year, with normal

[44] Jamaica (Hanover) and India (Narangwal) in the 1970s, India (Calcutta), Thailand and Haiti, in the 1980s.

growth rates being experienced after that (Shrimpton *et al.* 2001; Martorell 2008). Most of this lost growth cannot be caught up, and "even if a child catches up some lost growth, the effects of early childhood undernutrition on cognitive development and behavior may not be fully redressed. A stunted girl is likely to become a stunted adolescent and later a stunted woman. Apart from direct effects on her health and productivity, adult stunting and underweight increase the chance that her children will be born with [low birth weight]. And so the cycle turns." (Allen and Gillespie 2001, p2) This window of opportunity has led some researchers to argue that child health programs with a nutrition component that includes older children is not a good use of resources (Rohde 1993; Martorell 2008); most programs which include weighing children and promoting growth through counseling about health and nutrition target children up to five (as is the case with the *posyandu*) .

Thus the efficacy of most *posyandu* components has been established. The consequent question is whether they can be demonstrated at scale. Gillespie *et al.* (2007) consider the problem of scaling up health technologies. They identify eight under-five and maternal health interventions which are the most promising for scaling up (at an international level) when considering simplicity, compatibility, public health impact, observability, cost and relative advantage. Four of the *posyandu* components are included: measles vaccination, ORT, vitamin A supplementation and maternal tetanus toxoid immunization.[45] Thus health programs similar to the *posyandu* have the potential to be effective at a large-scale or national level. They note that "in general, the child and maternal health advocacy literature ignores or plays down the daunting challenges of taking an efficacious intervention to scale in resource poor settings" (p26). The next subsection reviews efforts to implement large-scale child health programs.

2.2.3 Interventions at scale

International institutional efforts to implement integrated or multiple component child health care programs at the national level have been substantial over the last three decades, beginning with UNICEF's GOBI initiative (growth monitoring, oral rehydration, breastfeeding and immunization) in the early 1980s and continuing with the WHO's IMCI (Integrated Management of Childhood Illness) from the 1990s into this decade. The integrated approach has now been introduced into most countries with moderate to high levels of child mortality (Bryce *et al.* 2005b). However, while the field efficacy of the various *posyandu* components has been established on a smaller scale, evidence of effective large-scale and national programs remains scant, in part, argue Bryce *et al.* (2008), because of a historical bias towards studies of the efficacy of specific interventions and against broader assessments of the effectiveness of program implementation. However, using randomized control trials for evaluating such large-scale interventions is usually impractical (Victora *et al.* 2004), and often not appropriate

[45] The other four are antibiotics for CB pneumonia case management, antimalarials, insecticide-treated materials (bed nets) and intermittent presumptive treatment for malaria.

for studying effects occurring a long time after the program (Habicht *et al.* 1999),[46] and most evaluations to date of large-scale programs have used aggregate trend data rather than being based on a careful micro-level study. In their summary of large-scale community-based programs, Mason *et al.* (2006) conclude that impact evaluation is sorely lacking, and that while the efficacy of the program components are established, changes in outcomes due to large-scale programs are unknown. Similarly, Caulfield *et al.* (2006) cite evaluations of the effect on child mortality of multi-faceted programs to reduce child undernutrition as a key gap in the scientific literature on program effectiveness. The current chapter is a contribution to such gaps. This subsection summarizes the extant studies on the large-scale child health program effectiveness.

Despite the widespread adoption of the GOBI approach in the 1980s, until recently there was very little evidence on the impact of multiple interventions on children under five (Allen and Gillespie 2001; WHO 2002). In 2001 the WHO initiated the IMCI Multiple Country Evaluation (IMCI-MCE), including feasibility assessments documenting the IMCI implementation in twelve countries and in-depth studies using compatible designs in Bangladesh, Brazil, Peru, Tanzania and Uganda. However, the lengthy study concluded that four of the five countries had difficulties implementing the strategy at a national level while maintaining adequate intervention quality (Bryce *et al.* 2005b), although Tanzania experienced a reduction in child mortality of 80 per 1,000 and a 30 percent fall

[46] Black (1996) also argues that observational studies are needed to complement randomized trials.

in malnutrition. A key conclusion of the study is that reliance on government health facilities is insufficient, and that a strong community-based approach is required.

Mason (2002) cites four successful national implementations: Thailand, Costa Rica, Tanzania and Indonesia. Thailand's national food and nutrition program was similar to the *posyandu* in that it used trained community-based volunteers and incorporated growth monitoring and nutrition education. Unlike the *posyandu*, food supplementation was also an important part. Malnutrition fell from 51 percent to 18 percent from 1982 to 1990 (Kachondam *et al.* 1992). However, these results are from an analysis of aggregate trends, as is the evidence for Costa Rica, Tanzania and Indonesia that Mason discusses, rather than a rigorous econometric study as presented in this chapter.

Ashworth *et al.* (2008) refers to evidence from larger programs in Tanzania (Iringa), Senegal and Madagascar that children whose growth is monitored and have access to basic health care, and whose mothers receive nutrition and health education, have a better nutritional and survival status than those who do not. However, none of this evidence is from careful micro-level evaluations. They also discuss the Tamil Nadu Integrated Nutrition program in India, which is amongst the most well-known of the large-scale multiple intervention programs and is often cited as an example of successful implementation at scale (e.g. Allen and Gillespie 2001). However, the evaluations used multiple approaches and the use of micro-level data with control and treatment groups was small in scale (Shekar 1992; Ashworth *et al.* 2008).

Thus, while many countries have implemented large-scale or national programs since 1980, they either experienced significant difficulties scaling up or have not been carefully evaluated. To my knowledge, this chapter is the first to demonstrate the large-scale effectiveness of a multiple-component child primary health care program using micro-level data.[47]

2.2.4 Increasing education and ability: competing interventions

This chapter also contributes to the literature on increasing the education component of human capital, which asks two related questions: (i) are interventions earlier or later in life more effective at improving education? and (ii) are health or education interventions more effective at improving education?

Early versus late interventions

Alan Krueger and Jim Heckman began a debate in 2002 as to how human capital (specifically employable skills) in the US can best be developed, with a particular focus on poor children (see Heckman *et al.* 2003). Each examine a range of specific policy

[47] Mexico's Progresa/Opportunidades program is now a national program and both much studied and imitated. However, it is not comparable to the programs discussed here since: (i) it is a conditional cash transfer program and targeted at the poor only; (ii) while one of the conditions is that children attend health clinics, the transfer of cash and the school enrollment requirements mean that any health and education effects cannot be identified as coming from the health component alone. Glewwe and Miguel (2008) exclude it from their survey of empirical evidence on the impact of child health on education for similar reasons.

interventions. Krueger (2003) supports a number of later interventions, such as class size reduction and job training for teenagers, in addition to early interventions such as pre-school programs. The shortfall in skilled workers, is not, Krueger argues, due to the design of current programs but their level of funding and credit constraints, and existing training and education programs should be expanded. Heckman and Carneiro (2003), in contrast, argue that there are high returns to early interventions and low returns to interventions later in life; that "skill and ability beget future skill and ability", meaning the highest returns to schooling and training are for the more able. That is, public investment should be directed not towards the expansion of schooling and training programs but towards early interventions such as pre-school programs. This argument is developed further by Carneiro *et al.* (2006), Cunha and Heckman (2007) and Heckman and Masterov (2007). While Krueger, Heckman and company debated this in the context of the US, it remains as pertinent to the developing world, if not more so, given fiscal constraints and limited development budgets.

A related question is whether health or education interventions should be preferred in promoting education and skill. Glewwe and Kremer note (2006:2), "First, additional children can be attracted to school at relatively low cost, either by reducing the cost of schooling and providing incentives for school attendance or by addressing basic health problems. Second, the evidence is mixed concerning the impact on learning of providing more educational inputs." A literature exists which examines the efficacy of different education and health policies on education outcomes in developing countries.

Summaries of education interventions can be found in Glewwe and Kremer (2006) and Orazem and King (2008), and of health interventions in Glewwe (2005) and Glewwe and Miguel (2008). A considerable body of empirical work has investigated both sets of interventions, but as both Behrmen (1996) and Glewwe and Miguel (2008) observe for the effect of health interventions on education, and Hanushek (1995) and Glewwe and Kremer (2006)[48] note for the effects of education interventions, much of the earlier work was cross-sectional in nature and did not address the numerous possible biases their research designs expose them to.[49] In the following review, I concentrate on the evidence from more recent studies, which draw on panel data or natural or randomized experiments.

Impact of health interventions on education

There is evidence that child health status as measured through height-for-age has positive effects on school enrollment and attainment. Alderman *et al.* (2001) use panel data and an instrumental variables approach to study the effects of child health status in Pakistan on education. They find that height-for-age at five years old has a strong positive effect on the probability of being enrolled at age seven, with one standard deviation of height-for-age leading to a 51 percent higher probability of a girl being enrolled in school at age seven and a 7 percent higher probability for boys. Glewwe *et*

[48] See also Kremer's (1995) comments on Hanushek.

[49] See Glewwe and Kremer (2006) and Glewwe and Miguel (2008) for comprehensive expositions of the problems facing such research designs.

al. (2001) also use panel data for the Philippines, along with sibling differences and an instrument to remove the effects of a child's innate ability. Their results suggest a one standard deviation improvement in height-for-age would reduce delayed enrollment by two months (similar to a three month response in Ghana found by Glewwe and Jacoby (1995)) and reduce the chance of repeating first grade by 9 percent. In another panel study using sibling differences, but with a quasi-experimental approach, early childhood height was associated with significantly greater young adult height (Alderman *et al.* 2006). The effects of this additional height on educational attainment were estimated at 0.28 extra years of completed schooling per centimeter of extra height, a large effect. Field and Robles (2006) studied an iodine deficiency treatment program in Tanzania, using a quasi-experimental approach with sibling differences. They found treated children were on average 0.31 years ahead in school, conditional on age. There was also suggestive evidence of higher passing rates on the primary school exit examination, to the degree of 22 percentage points for females and 14 percentage points for males.

Absenteeism can also be reduced by improved health status, in particular deworming. In randomized evaluations, a deworming program in Kenya reduced absenteeism by 7 percentage points and increased schooling by 0.15 years per pupil treated (Miguel and Kremer 2004), and deworming and iron supplementation in India decreased preschool absenteeism by 6 percent (Bobonis, Miguel and Sharma 2006). Bleakley (2002) estimated that before deworming in the early twentieth century in the US, each case of hookworm reduced the number of children attending school by 0.23.

However, evidence of the effectiveness of health programs on cognitive ability is more mixed. Glewwe *et al.* (2001) estimated that one standard deviation in height-for-age at enrollment was worth a 0.47 increase in test scores. Maluccio *et al.* (2006) found that exposure to the INCAP food supplement before the age of two in Guatemala was associated with 1.2 years increased schooling for women and a 17 percent increase in reading comprehension for both sexes, although the INCAP results in general are open to some criticisms, including significant attrition (see Glewwe and Miguel 2008). The Tanzanian iodine treatment in Field and Robles (2006) did not improve rates of illness or school absence due to illness, suggesting that the improved schooling attainment was through an effect on cognition rather than health (Field *et al.* 2008). Provision of school meals in Kenyan preschools increased participation by 30 percent, but academic test scores increased 0.4 standard deviations only with the inclusion of a teacher who was well-trained prior to the program (Vermeersch and Kremer 2004). Interestingly, there was no increase in cognitive test scores, implying that the academic improvements may have been due to increased time at school. The deworming in Kenya studied by Miguel and Kremer had no effect on test scores despite the increased attendance.

Impact of education interventions on education

Glewwe and Kremer (2006) review the more recent evidence on the effects of education interventions from natural and randomized experiments, the magnitudes of which are later compared to the *posyandu* effect on education. In general, while education interventions have been found to increase participation, it has been more difficult to improve test scores or cognitive ability. A combination of uniforms, textbooks and classroom construction in Kenya reduced dropout and increased years of education but did not affect grades (Kremer *et al.* 2002). While class sizes increased 50 percent as children transferred from nearby schools which may have affected results, another study of the provision of textbooks in the same area of Kenya found little effect on test scores, implying the change in class size had little effect either (Glewwe *et al.* 2003)[50]. Moreover, Banerjee *et al.* (2005) found halving the student-teacher ratio also had no effect on test scores in India. In addition, the use of flip-charts with instructional materials was not found to increase scores in Kenya (Glewwe *et al.* 2004).

Some education interventions have been found to improve student performance. Angrist and Levy (1999) found an increase in test scores from class size reduction (a one standard deviation reduction in class size (6.5 students) in Israel increased reading scores by 0.2 to 0.5 standard deviations and mathematics by 0.1 to 0.3).[51] Two remedial education programs in urban and rural India focusing on children with very low baseline scores were successful in improving test scores (0.6 standard deviation improvement) through a combination of an altered curriculum and motivated teachers (Banerjee *et al.* 2007; Banerjee *et al.* 2008). Duflo *et al.* (2008) also found that more motivated teachers may have been responsible for a 0.18 increase in test scores, and that teaching students

[50] They found textbook provision did not increase test scores for the average student, although this may have been due to language issues; a subset of students who scored well on pretests did see an increase.
[51] Throughout this section, as is standard in the literature, the effect of an intervention on test scores is measured in standard deviations of improvement in scores.

in groups with more homogeneous ability increased test scores by 0.14 for those in both higher and lower ranked classes. Glewwe, Ilias and Kremer (2003) found score-based teacher incentives in Kenya increased scores in the short term by 0.14 although the effects did not persist beyond the end of the program. In Israel, Lavy (2002) also found that student performance increased on the criteria in which teachers were given monetary incentives; students had 0.7 higher credits and were 2 percent more likely to sit their matriculation exam. Furthermore, attendance-based incentives for teachers not only reduced chronic absence in remote India from 40 to 20 percent, but also increased test scores by 0.17 (Duflo and Hanna 2005) .

Finally, restructuring of the education system can also increase student performance. While decentralization in El Salvador did not improve achievement (it did expand education to poor rural areas and reduce absenteeism; Jimenez and Sawada 1999), vouchers and school choice in Colombia increased scores on standardized tests by 0.2 at a marginal cost of $24 per voucher (Angrist *et al.* 2002) and these effects persisted over time (Angrist *et al.* 2006), although the evidence on vouchers in Chile is mixed (see Hsieh and Urquiola 2002, 2006; Contreras 2002 and Hoxby 2003). Thus, having summarized the evidence on the effectiveness of each of the *posyandu* components, we turn to the Indonesian experience in the following section.

2.3. The *Posyandu*

The *posyandu* (*Pos Pelayanan Terpadu*, or Village Integrated Service Post), formally introduced in 1985 but recognizable as such from 1980, was the national implementation of a community-based integrated child primary health care program. Originating from a pilot Village Family Nutrition Improvement Program (UPGK) in 800 villages in the late 1970s, the *posyandu* were a multisectoral effort promoting child welfare, run at a local level by the women's Family Welfare Program (PKK), with assistance from the Ministries of Health, Agriculture and Religious Affairs, and coordinated by the National Family Planning Board (BKKBN). The main political impetus for their expansion came from the realization that successful family planning required effective family welfare programs (World Bank 1983, 1985; Hull *et al.* 2007), acknowledged by Haryono Suyono, the long-term chairman of BKKBN who oversaw the development of the *posyandu* (Suyono 1991). The popular and successful village-based family planning program was integrated with growth monitoring and nutrition education, followed in the mid-80s by immunization as Indonesia committed itself to Universal Child Immunization (UCI) by 1990. Rohde (1993) gives a comprehensive account (see also Hull *et al.* 2007).

The *posyandu* program was a monthly health and nutrition meeting aimed at under-fives and run by village volunteers who received three to five days training. The main activities were immunization against six main childhood diseases,[52] done by a trained health worker, growth monitoring and nutrition education, oral rehydration salts (ORS) for diarrhea, and semi-annual high dose vitamin A. Family planning advice (including the need for birth-spacing) and contraceptive provision were also important functions, and iron-folic tablets were given to pregnant women for anemia prophylaxis.[53]

A notable aspect of the program is that it did not involve food supplementation; a small demonstration meal once per month was the only direct child nutrition intervention apart from vitamin A doses. Rather, growth monitoring was used to prompt education on appropriate breastfeeding and the use of complementary foods. This emphasis on monitoring and education meant a considerably less expensive program than similar large-scale efforts, both in Indonesia and elsewhere.[54]

Precursors to the *posyandu* expanded rapidly from about 800 villages in 1980 to 80,000 posts in half of Indonesia's 68,000 villages in 1986, to 20 million children enrolled in 250,000 posts in 1991, an 80 percent coverage of the target population (Rohde 1993; Department of Health's annual *Profil Kesehatan Indonesia* 1987-1992). The *posyandu*

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[52] As part of the Expanded *Program* on Immunization (EPI), which focused at the time on diphtheria, pertussis, tetanus, measles, tuberculosis and polio. The 1990 UCI target was successfully achieved with 80 percent of all children being immunized at their *posyandu* (WHO 1992).

[53] However, the family planning sevices predate the posyandu by over a decade, having been previously provided by village family planning posts.

[54] In addition, supplementary food programs without complementary services such as health care and education have had little impact on malnutrition (Beaton and Ghassemi 1982); see Rogers (2002) for discussion.

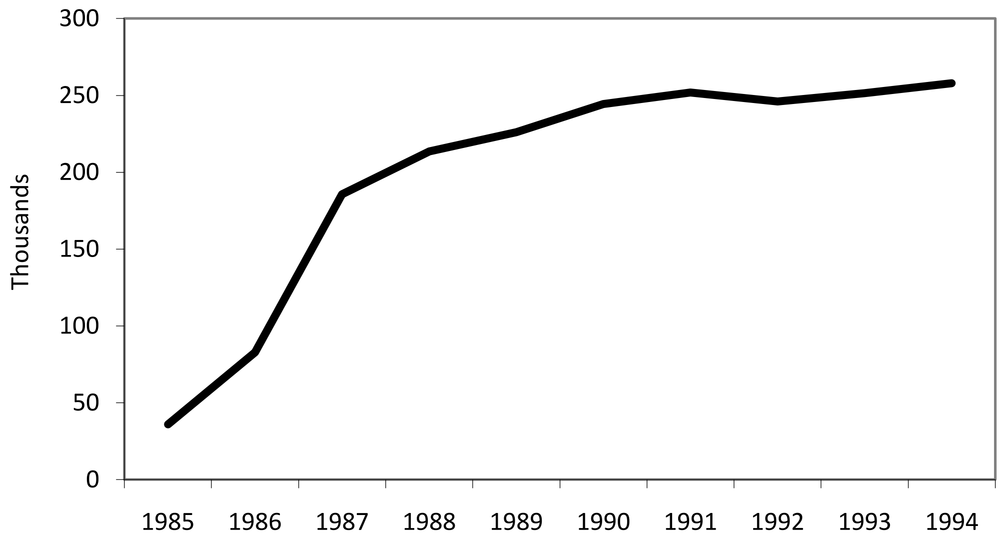
effectively ended as a national program with the Asian Crisis of 1997-98, although they continued in many regions and there has been interest in their revitalization since 2000. Figure 2.1 shows their growth over time.[55]

A four province UNICEF study in 1989 found 80 to 98 percent enrollment in the *posyandu*, with 35 to 70 percent of children attending monthly and 46 to 52 percent gaining weight (Rohde 1993). The average attendance rate over the 0-4 year old range hides excellent participation from those who would benefit the most: an 80 to 90 percent attendance rate amongst those in their first year of life and a 75 to 90 percent attendance by those in their second year. Participation falls off rapidly in older children. I present usage rates from my own data in the next section; attendance patterns are similar, albeit lower.

The cost of the program has been estimated between 2 and 11 US dollars per child per year (Rohde 1993; Mason *et al.* 2006), which makes it one of the least expensive interventions in the literature. A more detailed examination of the program's cost-effectiveness is presented in Section 2.6.

[55] National data on *posyandu* numbers before the beginning of the official program in 1985 are not available.

Fig. 2.1. Growth of *posyandu* over time



Source: Indonesia Health Profiles 1988-1995, Department of Health

2.4. Data and Empirical Strategy

2.4.1 Indonesian Family Life Survey

The Indonesian Family Life Survey (IFLS) is used for the majority of the analysis in this chapter. It is a longitudinal socioeconomic and health survey conducted in 13 of Indonesia's then 27 provinces, representing 83 percent of the population (Frankenberg and Karoly 1995; Frankenberg and Thomas 2000; Strauss *et al.* 2004). There have been three waves; 1993, 1997 and 2000, with a 1998 supplemental survey of a quarter of the households in the immediate aftermath of the Asian financial crisis.[56] The IFLS is a very rich dataset, with detailed individual and household information, including modules on

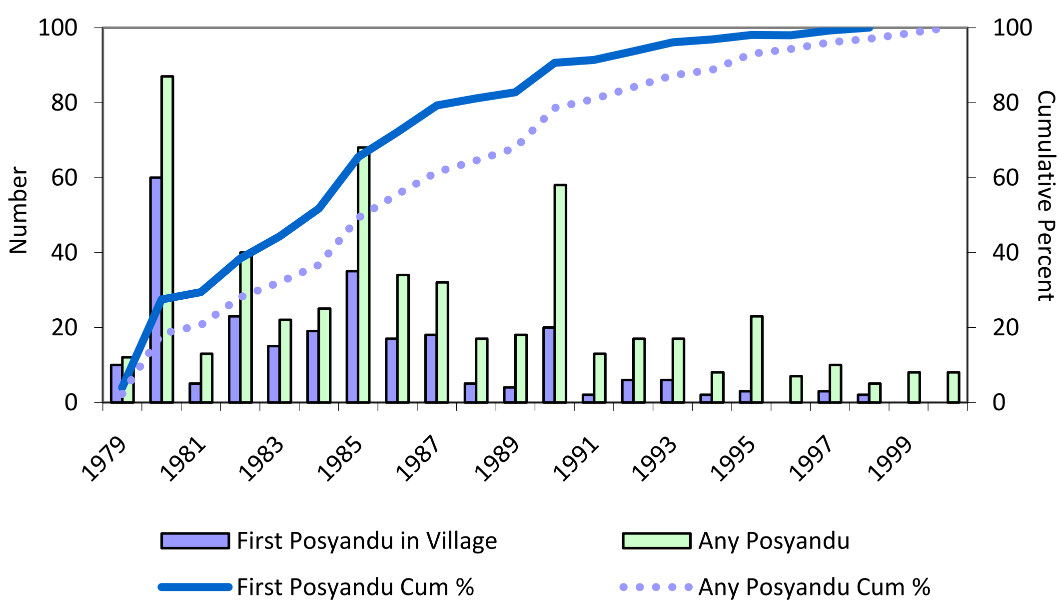
[56] A fourth wave was fielded in 2007 and is in the process of being made publicly available at the time of writing.

consumption, income and assets, education, migration, labor market outcomes, marriage and fertility, health and health care, and household decision-making and intra-family transfers. It also includes community data on infrastructure, employment opportunities, food prices, and access to health and educational facilities. 10,435 households are in the 2000 survey (48 percent urban, 52 percent rural), with 14,129 female adults, 12,997 male adults and 11,307 children interviewed.

This chapter relies heavily on three questionnaires from the IFLS survey. First, I use information on children aged 0-14 including anthropometric data, illnesses and injuries suffered in the last four weeks and recent outpatient treatment and hospitalization, as well as immunization, breastfeeding and *posyandu* attendance and utilization data for 0-5 year olds. Test results from national subject tests in Indonesian, mathematics, science, social studies and moral education are available for 10-14 year olds in 2000. Parents' education and household consumption, income and wealth data are also constructed from the IFLS. Second, the questionnaires for ever-married women 15-49 years provide data on pregnancy histories (number of pregnancies, live and stillbirths, gestation periods, birth order, health facility utilization and child mortality outcomes), and breastfeeding practices. Finally, from the community data I constructed a history for each village of health facilities (hospitals, health centers, *posyandu*, midwives and doctors), education facilities (number of primary and secondary schools), infrastructure (sewage, solid waste collection, availability of public transport, piped drinking water) and social enterprises (rotating credit associations and child development groups). It should also be noted that I employ non-publicly available IFLS variables. In particular, information on location of birth at a village level (along with year of birth) enables me to determine whether a *posyandu* was available when a child was born.[57]

Figure 2.2 shows the year each *posyandu* began in IFLS communities. We can see that villages receiving their first *posyandu* are clustered around 1980 (the beginning of the pilot program), 1985-87 (the beginning of the national program) and 1990 (the end of what might be considered the national escalation). Around 50 percent of IFLS villages receive their first *posyandu* during the pilot phase, about 40 percent over the national roll-out and the remainder over the 1990s until the Asian Crisis of 1997-98.

Fig. 2.2. Year p*osyandu* began by village in IFLS sample



Source: IFLS 2000.

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[57] Many thanks go to Kathleen Beegle and John Strauss for making these data available to me.

2.4.2 Other data

I supplement the IFLS data with other data sources. Provincial level health, education and economic data were taken from the Department of Health's annual Indonesian Health Profile reports. Implementation data on the *posyandu*, such as district enrollment, attendance and weight gain rates were obtained from the Family Planning Coordination Board (BKKBN). These are employed to control for variations in program quality and utilization over different districts and time.

2.4.3 Empirical strategy

As Victora *et al.* (2004) observe, when evaluating a large-scale intervention, randomized control trials are often not feasible and plausibility studies or quasi-experimental designs may be the only evaluations possible. To evaluate the effects of the *posyandu*, I exploit geographic and temporal variation in program implementation as an identification strategy. Data on place and year of birth allow me to determine whether a *posyandu* was operating when any particular child was born.

Throughout the analysis I perform two general estimations. The first attempts to identify the size of any *posyandu* treatment effect:

$$Y_{ijt} = \alpha + \beta X_{ijt} + \gamma T_i + \phi C_{jt} + \delta_j + \mu_t + \varepsilon_{ijt} \qquad (1)$$

where *i, j, t* represent individuals, village of birth and birth year respectively, Y_{ijt} the dependent variable of interest, X_{ijt} individual characteristics, C_{jt} village characteristics at time of birth, and δ_j and μ_t are village[58] and year of birth dummies respectively. T_i is the explanatory variable of interest, a cohort treatment dummy. Errors are clustered at the village- or household-level depending on the variable of interest. Common controls at the individual level include child's age, sex, urban location, parents' education, a variety of illness symptoms over the past four weeks and whether the child was fasting; income, wealth, food and non-food consumption at the household level; and community infrastructure in year of birth, such as sub-district health centers, solid waste and sewage disposal, piped drinking water, and public transport.

This approach is similar to a difference-in-differences estimation. If all *posyandu* were established at the same time, then a significant coefficient on T_i might reflect not only a possible *posyandu* effect, but also national socio-economic trends or unobserved village-specific effects. The use of year-of-birth and village dummies captures national trends and time-invariant village effects respectively. C_{jt} represents those time-varying community variables explicitly included as controls. Thus, as with difference-in-differences, only unobserved time-variant village-specific effects which moreover occurred at the same time in the same village as the *posyandu* remain uncontrolled for. This is discussed further in Section 2.5.

The second estimation is used to understand the timing of *posyandu* effects:

$$Y_{ijt} = \alpha + \beta X_{ijt} + \gamma \Sigma_t A_{ijt} + \phi C_{jt} + \delta_j + \mu_t + \varepsilon_{ijt} \qquad (2)$$

[58] Village is used to refer here to both villages in a rural setting and neighborhoods in an urban context.

and replaces the cohort treatment dummy with $\Sigma_t A_{ijt}$, a series of relative age dummies representing the number of years a *posyandu* has been operating in the village by the year of birth. For example, a child born the same year as a village first received a *posyandu* would have a relative age of 0; one born four years before the *posyandu* began would have a relative age of -4 and one born three years afterwards would have a relative age of 3. We would expect children born before a *posyandu* first began operating in their village to experience a smaller effect on their health. Given the opportunity to alleviate the effects of malnutrition is greatest *in utero* and from 0 to 2 years old, we would expect to see *posyandu* treatment effects beginning in children with a relative age of about -2, with little or no effect before then and an increasing effect afterwards.

2.5. Results

2.5.1 Differences in timing of posyandu *implementation*

My identification strategy utilizes variations in the timing of *posyandu* establishment. Provincial data shows there were early and late adopters. For example, in 1987, the third year of the national roll-out, eight provinces had over 70 percent of their 1990 *posyandu* numbers, nine had 50 to 70 percent, and seven had under 50 percent.[59] Figure 2.3 shows the number of children aged 0 to 5 years served per *posyandu* by province as a ratio to the national average.

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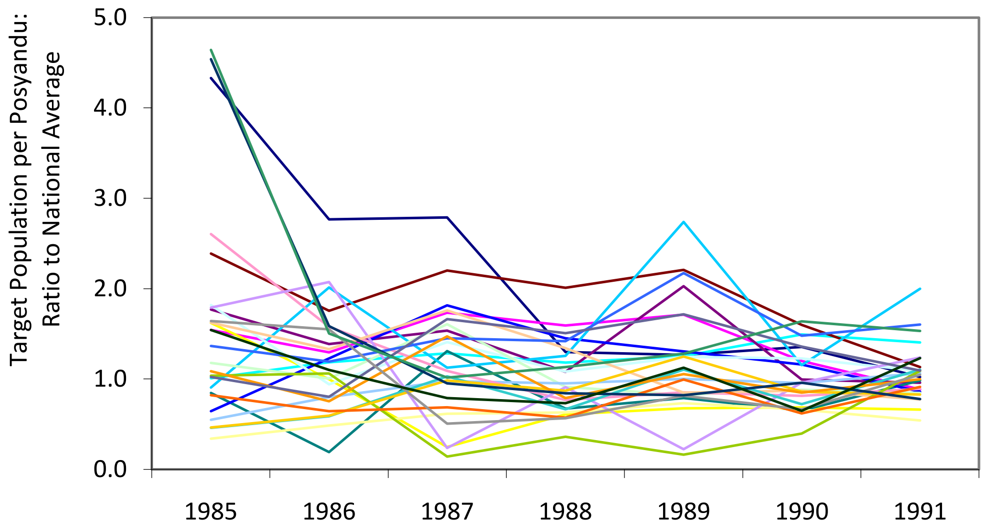
[59] Data calculated from the Department of Health's Indonesia Health Profile annual series.

Fig. 2.3. Children aged 0-5 years served per *posyandu* by province: provincial ratio to national average

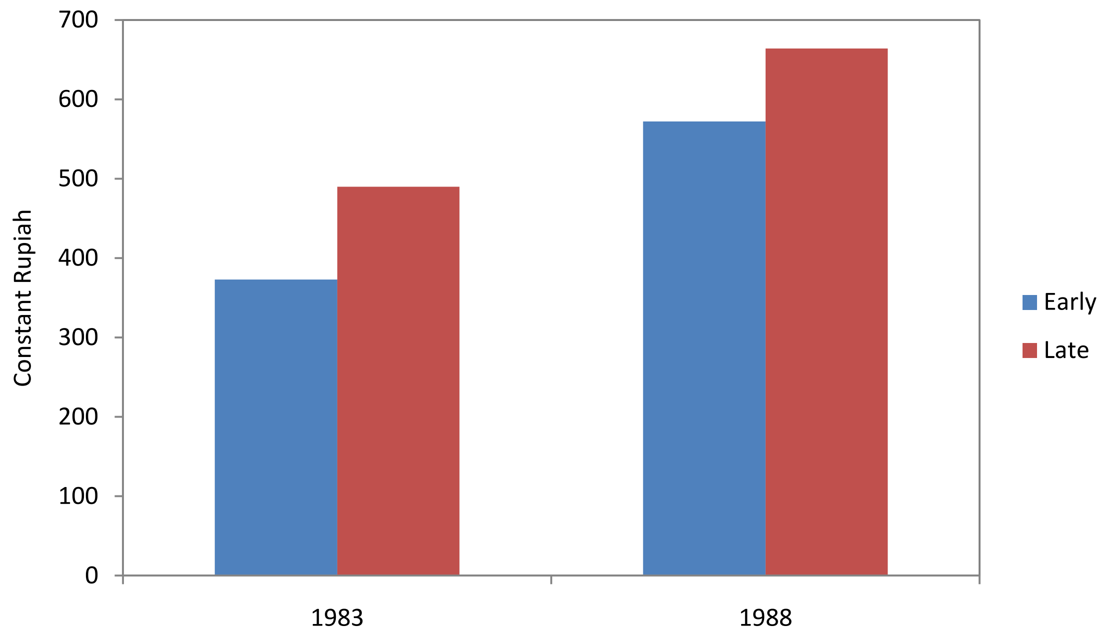


Source: Author's calculations, Indonesia Health Profiles 1988-1995, Department of Health

A number of provinces in 1987 have a ratio less than one; that is, they have more *posyandu* per child than average. Similarly, there are also provinces with more than the national average of children per *posyandu*. An important issue, then, is what determined these differences in timing and whether villages getting *posyandu* earlier were systematically different from villages receiving them later, such as being wealthier, better politically connected, or better developed. Figure 2.4 presents differences between early and late adopters. I consider early adopters to be those provinces with less children per posyandu relative to the national average by 1988. We can see provinces getting more *posyandu* earlier were slightly poorer, but with little difference in per capita health spending and similar levels of infant mortality and malnutrition.

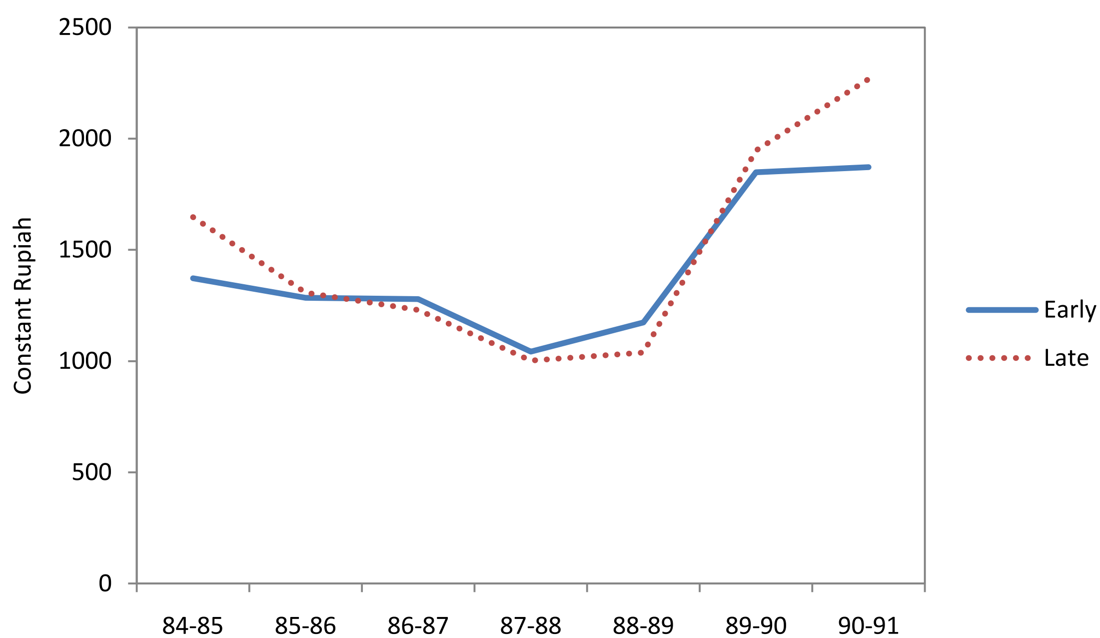
Fig. 2.4. Provincial differences in early and late posyandu adopters.

A: Regional product per capita 1983-1988



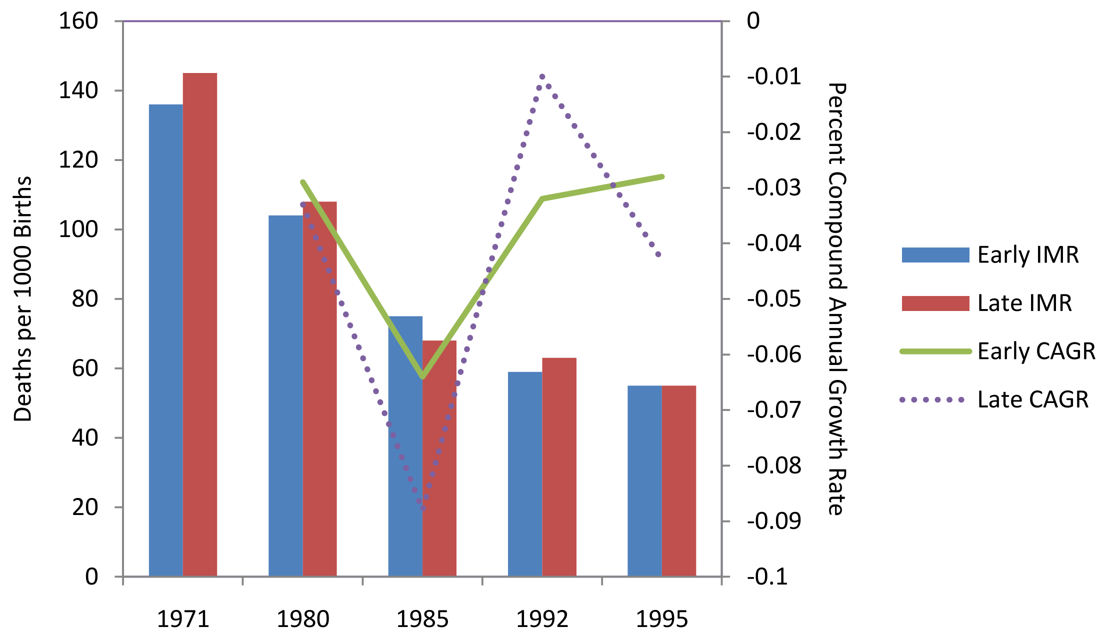
Source: Author's calculations, Indonesia Health Profiles 1988-1995, Department of Health

B: Health spending per capita 1984/85-1987/88



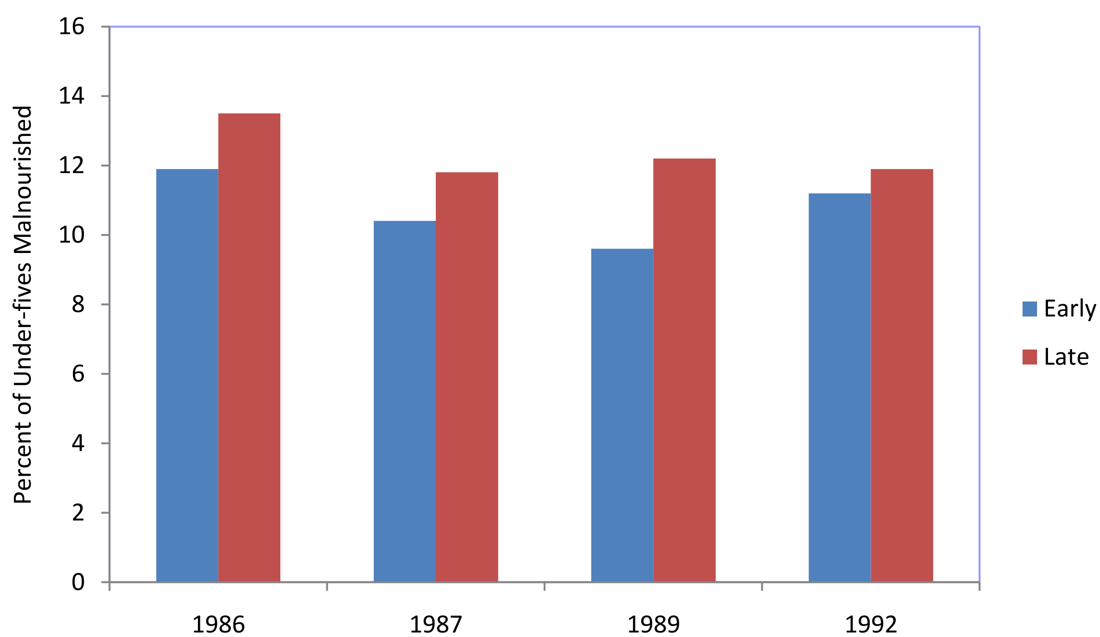
Source: Author's calculations, Indonesia Health Profiles 1988-1995, Department of Health

C: Infant mortality rates 1971-1995



Source: Author's calculations, Indonesia Health Profiles 1988-1995, Department of Health

D: Malnutrition rates 1986-1992.



Source: Author's calculations, Indonesia Health Profiles 1988-1995, Department of Health

We can also look at differences between early and late adopters at the village level within the IFLS sample. Table 2.1 examines differences in infrastructure at the time of the first *posyandu* between early adopters (1987 and before) and late. Generally, little significant difference exists. Where there are differences, later adopters tend to have better infrastructure by the time of their first posyandu; they are more likely to have sewage and solid waste disposal and slightly more schools (although not at a primary school level). In results not shown, early adopters were more likely to be urban; 69 percent of *posyandu* in urban areas started before before 1988, whereas only 51 percent of *posyandu* in rural areas did.

Thus there is generally little difference between early and late adopters of *posyandu*; where differences exist, late adopters tend to be richer or more developed. Whether this indicates that poorer areas were targeted earlier is unclear.

2.5.2 Use of posyandu *by age cohort*

Table 2.2 summarizes attendance rates in the IFLS data for children aged 0-5 years, and the treatments the attendees received. Data are only available for 1997 and 2000. Attendance in the previous four weeks is around 50 to 60 percent for children under two years, which is lower than the 75 to 90 percent estimated in four provinces by UNICEF in 1989. Similarly to the UNICEF study, participation falls rapidly for older children. Of those attending, most are weighed and many immunized. Vitamin A supplements, given every six months, are received by 37 to 68 percent of attendees,

Table 2.1. Village-level differences between early and late adopters

	1985 Means			1990 Means			Means at Year of First Posyandu		
Infrastructure	Early	Late	t-test	Early	Late	t-test	Early	Late	t-test
Health center	0.93	0.98	0.07*	0.97	1.00	0.07*	0.94	0.96	0.48
Sewage disposal	0.18	0.33	0.03**	0.25	0.41	0.02**	0.26	0.21	0.49
Solid waste disposal	0.02	0.2	0.00***	0.12	0.27	0.01**	0.12	0.13	0.84
Public transport in village	0.47	0.5	0.68	0.55	0.55	0.97	0.45	0.58	0.10*
Public transport out village	0.13	0.12	0.86	0.18	0.18	0.94	0.11	0.15	0.44
Piped drinking water	0.20	0.3	0.14	0.32	0.42	0.16	0.22	0.33	0.11
Village midwife	0.03	0.03	0.96	0.12	0.11	0.96	0	0.13	0.00***
Arisan	0.15	0.19	0.49	0.23	0.33	0.14	0.12	0.21	0.09*
Dana sehat	0.00	0.07	0.03**	0.10	0.14	0.38	0.03	0.1	0.98
Number of schools	5.32	5.87	0.03**	5.90	6.53	0.01***	5.33	6.04	0.01***
Number of primary schools	2.60	2.69	0.40	2.70	2.86	0.09*	2.55	2.67	0.33
Observations	201	60		201	60		201	52	

Notes: t-test for difference of means.
* significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.
Source: Author's calculations from IFLS 2000

suggesting attendance may be higher in months when vitamin A is handed out, particularly amongst older cohorts. Oral rehydration salts are received by 6 to 19 percent of children.

Table 2.2. Posyandu use by target population

			Proportion of attendees who received:			
Age	N	Attended	Weighed	Immunized	Vitamin A	ORT
			1997			
0	517	0.56	0.88	0.82	0.39	0.10
1	593	0.59	0.90	0.74	0.55	0.12
2	601	0.52	0.90	0.69	0.63	0.17
3	587	0.49	0.82	0.69	0.54	0.17
4	710	0.40	0.81	0.72	0.63	0.16
5	662	0.18	0.74	0.64	0.54	0.16
			2000			
0	962	0.53	0.98	0.71	0.37	0.06
1	816	0.47	1.00	0.45	0.58	0.15
2	767	0.35	0.99	0.37	0.66	0.12
3	754	0.29	0.96	0.30	0.62	0.12
4	801	0.21	0.96	0.27	0.66	0.18
5	713	0.04	0.97	0.42	0.68	0.19

Notes: N is the number of observations in each age-year cohort. Attended is the number in each cohort who attended a posyandus in the last four weeks. Weighed, immunized, vitamin A and ORT are the proportion of attendees in the last four weeks who were, respectively, weighed, immunized, given a vitamin A supplement and received oral rehydration salts.
Source: IFLS 1997 and 2000.

2.5.3 Impact of the posyandu

This section estimates the impact of the *posyandu* program. I first examine the general effect on child malnutrition, before looking at changes in breastfeeding behavior and the effect on mortality, finally turning to test scores for those aged 10-14 years. Data from two different respondent types are used for these analyses. Malnutrition and education outcomes are drawn from data collected on children aged 0-14 years, whereas breastfeeding behavior and child mortality outcomes use information from ever-married women aged 15-49 years and their pregnancy summaries.

Malnutrition

I estimate the effect of the *posyandu* in reducing child malnutrition, which is attributable predominantly to growth monitoring and nutrition education and ORT[60] (the other components generally have survival effects rather than nutrition effects); Table 2.3 presents the results. Both underweight and stunting are used as indicators of malnutrition, and a dichotomous variable for each is regressed upon a full set of individual, household and time-varying village controls, as well as village and year of birth dummies, and a cohort dummy (this estimates equation 1). The cohort dummy takes 1 if relative age is between -2 and 3 (children born two years before the *posyandu* until three years after the *posyandu*), and 0 if between -7 and -4 (children born four to seven years before the *posyandu*). The coefficient on the cohort dummy represents the *posyandu* effect. Columns 1-4 have underweight as the dependent variable and columns 5-8 have stunting. Columns 1 and 5 include no controls, columns 2 and 6 use the individual and households controls and village and year of birth fixed effects, while columns 3-4 and 7-8 include the time-varying village controls as well.[61] Errors are

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[60] Repeated bouts of diarrhea are associated with growth faltering (Behrman *et al.* 2004).

[61] The full set of controls are individual (age, sex, urban, whether fasting at time of survey, parents' education, whether child suffered from a variety of illnesses in the last four weeks), household (wealth, income, food and non-food consumption) and time-varying village (whether at the time of birth there was a community health center, public transport, piped drinking water, sewage disposal and solid waste disposal).

clustered at the community level. The full specifications for underweight, in columns 3 and 4, estimate a reduction in probability of wasting of 20 to 26 percent (using a linear probability and probit model respectively), while the probability of stunting is reduced by 19 to 22 percent (columns 7 and 8).[62]

These results are robust to different definitions of the treatment and control cohorts, restriction to those villages with children born both before and after the *posyandu* and type of regression model, as seen in Tables 2.10-12 in the appendix. Moreover, we can conduct a falsification experiment. Ideally we could treat two cohorts born before the *posyandu* as treatment and control, neither of which should benefit from the program; a spurious positive coefficient on the treatment dummy would indicate that the cohort dummy was actually picking up an underlying village-specific time trend in malnutrition distinct from the *posyandu*. Since we do not have sufficient control data to conduct this analysis, I instead present a similar experiment where I compare two cohorts born *after* the *posyandu*, treating one as the control group. As both groups were in fact treated, we should not get a significant coefficient on the treatment dummy. As Table 2.11 shows in columns 7-9, this coefficient is very small and insignificant over a range of cohort definitions.

Figure 2.5 presents the coefficients on the relative age dummies (and their 95 percent confidence range) when substituted for the treatment cohort dummy, in order to

[62] This is similar to the 30 percent fall in malnutrition found in the Tanzanian program, and less than the undocumented initial estimate of 50 percent for the Integrated Child Care Program in Honduras (Behrman *et al.* 2004).

understand the timing of the *posyandu* effect. (This is estimating equation (2) rather than (1)). Take, for example, the likelihood of a child being underweight. For those born four to eight years before a *posyandu* (relative age of -4 to -8), we see no difference in the likelihood of being underweight than those born nine years before. The coefficient on those born three years before is slightly negative but not significantly different from zero. However, for children born two years before a *posyandu* or later, which is the beginning of the malnutrition intervention window of opportunity, the likelihood of being underweight is reduced by 20 percent or more (significant at the 95 percent level). The probability of stunting shows a similar pattern (if less precisely estimated). This sharp trend break in the relative age coefficients is strong evidence that the reduction in malnutrition we are identifying is indeed attributable to the *posyandu*, since the timing of the effect is consistent with the medical literature as previously discussed. As well as a sharp trend break at a relative age of -2, we also see a slight tendency for the relative probabilities of underweight and stunting to decline for children born even later. This could reflect learning on the part of the *posyandu* volunteers, or perhaps the effect of increased duration in breastfeeding which lagged the overall malnutrition effect as discussed later. These results are robust to changes in the relative age range used in regressions and the span of each dummy (see Figures 7-8 in appendix).

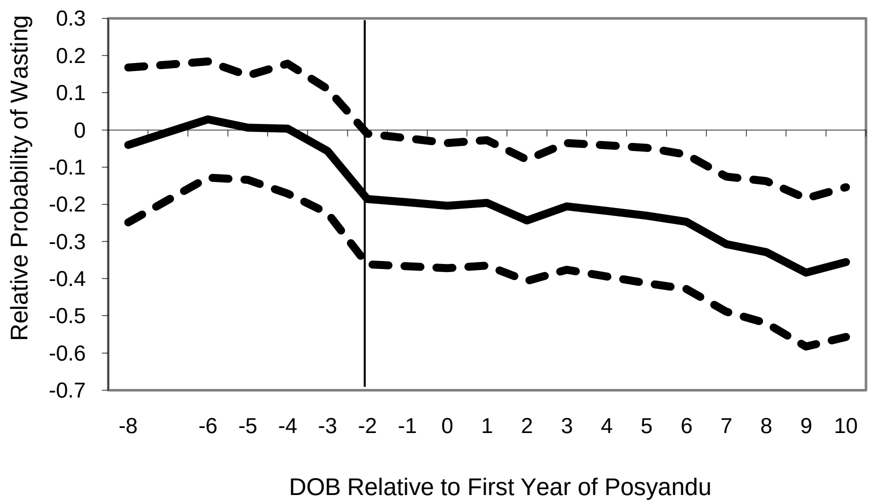
Table 2.3. Reduction in malnutrition

	Underweight				Stunting			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Posyandu effect	-0.10**	-0.10**	-0.20***	-0.26***	-0.10***	-0.12***	-0.19***	-0.22***
	0.025	*0.021*	*0.002*	*0*	*0.011*	*0.001*	*0.002*	*0.001*
Individual controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	No	Village	Village	Village	Village	Village	Village	Village
Year of birth FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time-varying village controls	No	No	Yes	Yes	Yes	No	Yes	Yes
Type of regression	LP	LP	LP	Probit	LP	LP	LP	Probit
Observations	2,144	2,048	2,048	1,923	2,144	2,048	2,048	1,972

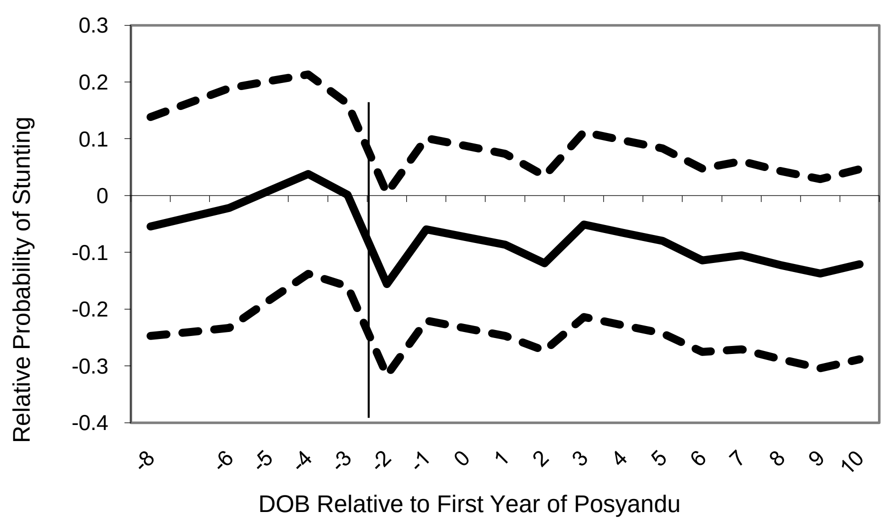
Notes: Sample is children aged 0-14 years.
* is significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent. P-values are reported in italics.
LP is linear probability model. Posyandu effect is coefficient on cohort dummy, which takes 1 if relative age is -2 to 3 and 0 if -7 to -4.
Includes village and year of birth dummies. Individual controls are child's age, sex, urban, whether fasting at time of survey, parents' education and whether child suffered from a variety of illnesses in the last four week. Household controls are household wealth, income, food and non-food consumption. Time-varying village controls are whether at time of birth there was a sub-district health center, public transport, piped drinking water, sewage disposal, solid waste disposal.

Fig. 2.5. *Posyandu* effect on malnutrition by relative age

A: Wasting



B: Stunting



To what extent were the *posyandu* responsible for the reductions in malnutrition observed in Indonesia? This is not easily estimated; baseline data were not well collected. But severe malnutrition declined from between 30 and 50 per 1,000 children in the mid-70s to 10 by the early 1990s (Rohde 1993). If we take that to mean children were 67 to 80 percent less likely to be malnourished, then the *posyandu* contributed to at least a quarter to a third of that (20 to 25 percentage points in Table 2.3).

Child Mortality

With malnutrition being the underlying cause for 35 to 60 percent of all child mortality, we would expect the substantial reduction in malnutrition due to the *posyandu*, along with the mortality reducing treatments of immunization, vitamin A supplementation and ORT to reduce mortality as well. Table 2.4 presents the effect of the *posyandu* on child mortality. A dichotomous variable for whether a child was alive by a certain age is the dependent variable. This is regressed on the *posyandu* treatment dummy (the explanatory variable of interest), individual controls (sex, urban, mother's age at birth, mother's education, maternal height, gestation period, birth order, whether a multiple birth), time-varying community controls (dummies for whether at the time of birth the village had a community health center,[63] sewage, solid waste disposal, public transport, and piped drinking water), as well as village and year of birth fixed effects. Errors are clustered at the village level. Children born after a posyandu began operating in their village were 2.6 percent more likely to be alive by the age of one than those born before, 3.6 percent more likely by the age of five and 4.6 percent at the time of survey.

[63] A health center, or *puskesmas*, is a health center located on average at a rate of one per subdistrict. They have medical staff available (doctors and nurses) and sometimes hospital beds.

It should be noted that the statistical significance of results is less than for those of malnutrition. A contributing factor is the differing nature of data. While the malnutrition analysis used data from current measurements of children's weight and height, the mortality analysis (and breastfeeding analysis in the next subsection) draws upon pregnancy summaries of ever-married women. Such data necessarily is recall data and consequently more prone to measurement error, particularly with respect to the year of a child's birth and death, and the duration of breastfeeding.

7 percent of live births in the sample were dead by one years old, meaning the 2.6 percent lower chance of death due to *posyandu* represents a 37 percent lower infant mortality within the sample. This is very consistent with the fall in infant mortality rates in Indonesia over this time which fell from 112 per 1,000 births in 1980 to 41 in 1997;[64] a 26 point reduction attributable to the *posyandu* would represent 37 percent of this national reduction in infant mortality as well. Similarly, 9 percent of live births in the sample were dead by five years old, so the 3.6 percent lower chance of death due to *posyandu* represents a 40 percent lower child mortality within the sample. Child mortality rates for Indonesia are not available over the same period, but assuming the same proportional gap between infant and child mortality rates in 1980 and 1997 as in 2000, a 36 point reduction due to the *posyandu* would represent 39 percent of the national reduction in child mortality.

[64] Thus achieving the Ministry of Health goal set in the early 1980s of an IMR of 45 by 2000 (World Bank 1983).

The results in Table 2.4 are robust to a range of specifications and models. Significance and magnitude on the cohort dummy remain similar over different ranges of ages relative to *posyandu* control and treatment groups, and including current household wealth does not change results.

The coefficients in Table 2.4 also suggest that the *posyandu* effect on mortality increases over time, with about half of the total reduced likelihood of mortality being achieved by the age of one, and three quarters by the age of two. In analysis not presented here, low birth weight was used as the dependent variable, with no significant result on the treatment variable, indicating that the malnutrition and mortality results are being driven by the effect of the *posyandu* components on the child after birth, not through possible channels such as improved maternal nutrition due to nutrition education.

While the data do not allow a decomposition of the reduction in child mortality by *posyandu* component, we can check the consistency of the results with known efficacy rates for all components. Table 2.5 estimates the reductions in mortality expected from each component using the field efficacy results from the literature discussed in Section 2.2, and subtracting estimated interactions between the components to calculate a predicted aggregate effect from the *posyandu* program. For example, reading along the top line of Table 2.5, the Southeast Asian child mortality rate is 80 per 1,000 (WHO 2003). Diarrhea is the cause of 15 percent of child deaths, or thus about 12 per 1,000.

ORT has been found to be 75 percent effective in preventing these deaths (extrapolated from Victora *et al.* 2000). Assuming all children with diarrhea received ORT from a *posyandu*,[65] then the predicted reduction from this component of the *posyandu* is about 9 points (that is, 75 percent of 12). Predicted reductions from immunization against measles, pertussis and tetanus can be calculated similarly (using immunization coverage rates from the IFLS). However, when calculating vitamin A and nutrition education effects, we need to account for the interactions with diarrhea and measles. Vitamin A increases child survival by 25 to 35 percent (thus reducing mortality by 20 to 28 deaths per thousand children), but this effect is due in part to reductions in diarrheal deaths (50 to 71 percent) and measles deaths (33 to 46 percent) (Beaton *et al.* 1993; Bryce *et al.* 2005a; UNICEF 2009). Thus the diarrheal- and measles-independent reduction in mortality due to vitamin A (excluding the diarrheal mortality rate of 12 points times 50-71 percent cofactor, or 6.1-8.6 points, and the measles mortality rate of 4 points times 33-46 percent cofactor, or 1.4-2.0 points) is 20-28 less 10.6-7.5 cofactor effect, or 9.4 to 20.5 per thousand. Similar calculations can be done to estimate the independent nutrition effect. The resulting predicted reduction in child mortality given the clinical efficacy of the *posyandu* components, after controlling for their interactions and the usage of each component, is 27 to 45 points. This is consistent with the 36 point estimate in Table 2.4.

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[65] By 1990, Rohde (1993) reports that "knowledge of ORT is universal, with high ORS use rates and a sharp decline in dehydration as a cause of hopstpitalization or death."

It should be noted that this mortality effect also creates a selection bias in our estimated 20 to 25 percent reduction in malnutrition, which likely causes it to be understated. As Rohde (1993, p.150) notes, "one must take into consideration the dramatic decline in mortality and the consequent likely rise in undernutrition attendant upon such improved survival. Those who would most likely have died in the 1970s under prevailing mortality levels were disproportionately the undernourished, who are surviving today." That is, average malnutrition is increased amongst the cohort born after the *posyandu* by the presence of malnourished children who would otherwise have died before their fifth birthday without the mortality reducing effects of the *posyandu*. Children born after a *posyandu* who survive are *on average* 20 to 25 percent less likely to be malnourished than those born before a *posyandu*; those who would have survived anyway will be even less likely again to be malnourished. Non-*posyandu* reductions in mortality may have contributed to an even further understatement of *posyandu* effects on malnutrition.

One final point of interest with respect to the reduction in infant and child mortality is the role of maternal and paternal education. From 1973 to 1977 Indonesia embarked on the largest primary school building program in history. The effects on education, income and inequality have been well-documented by Duflo (2001, 2004). In addition, Breierova and Duflo (2004) have also examined the effects of the school building program on child mortality. In their sample, 0.16 children per mother died by the age of one and 0.21 before they were five. They find the school building program reduced the number of infant deaths per mother by 0.06 and under-five deaths per mother by 0.09, implying reductions in mortality equivalent to 38 percent and 43 percent of the average sample mortalities. If the mortality reducing effects of the school building program and the *posyandu* were independent, together they would account for 75 percent of infant mortality reductions and over 80 percent of under-fives.[66]

Breastfeeding

As discussed, it is difficult to disentangle the effects each of the *posyandu* components may be having on malnutrition and mortality. Moreover, there are insufficient data to test the *posyandu* effect on most components individually. However, a significant element of the nutrition advice regards breastfeeding, a major channel through which reductions in mortality and malnutrition might occur (see Section 2.2), and the maternal history data of the IFLS include duration of breastfeeding. Table 2.6 presents results from a similar regression to the malnutrition analysis, with number of months an infant

[66] The school building program began around twelve years before the national initiation of the *posyandu*. Thus a child of six entering primary school in 1973 would be 18 in 1985; potentially many of the mothers and fathers of children who attended *posyandu* were beneficiaries of the school program. While this is implicitly controlled for in all of my analysis through the inclusion of parental education as an independent variable, it is possible that the school program had an indirect affect on the communities they were built in which might also have had an impact on child mortality and malnutrition in later years. However, explicitly controlling for whether the district of birth was intensively exposed to the school program in my analysis only slightly reduces the *posyandu* effect in magnitude and significance.

Table 2.4. Reduction in child mortality - probability of being alive

Dependent Variable: Alive at:	At survey	1 year	2 years	3 years	4 years	5 years	10 years	14 years
Posyandu effect	0.046**	0.026	0.034*	0.036*	0.036*	0.036*	0.033*	0.038*
	0.014	*0.118*	*0.072*	*0.056*	*0.064*	*0.058*	*0.091*	*0.062*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Village	Village	Village	Village	Village	Village	Village	Village
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,618	4,618	4,618	4,618	4,618	4,618	4,618	4,618

Notes: * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.
Sample is children born between 1970-2000 to ever-married women aged 15-49 years.
Posyandu effect is whether born after first year of posyandus in village. Errors are clustered at the household level. Individual controls are mother's age at birth, urban, mother's education, mother's height, period of gestation, multiple birth, birth order. Household controls are household wealth. Time-varying village controls are whether at time of birth there was a sub-district health center, public transport, piped drinking water, sewage disposal, solid waste disposal. Includes village and year of birth dummies.

Table 2.5. Implied reduction in mortality from efficacy of components

Posyandu component	Cause of death addressed	Childhood mortality rate (per 1000)	Deaths due to cause (%)	Mortality rate from cause (per 1000)	Efficacy of intervention (%)	Usage of intervention (%)	Implied mortality reduction (per 1000)
ORT	Diarrhea	80	15%	12	75%	100%	9
Immunization	Measles	80	5%	4	85-90%	68%	2-3
	Pertussis	80	3%	2	70-90%	79%	1-2
	Tetanus	80	2%	1	80-95%	75%	1

Notes: Some figures will not add exactly due to rounding.
Sources: Under-five mortality from WHO (2003); ORT efficacy extrapolated from Victora *et al*. (2000); immunization efficacy from Brenzel *et al*. (2006); immunization usage from IFLS; increase in survival from vitamin A from Allen and Gillespie (2001) and Beaton *et al*. (1993); diarrhea and measles co-factors from Beaton *et al*. (1993); Bryce *et al*. (2005a) and UNICEF (2009); malnutrition as cause of mortality from Ashworth *et al*. (2008); efficacy of posyandus intervention from this chapter.

Table 2.5. Continued

Posyandu component	Cause of death addressed	Childhood mortality rate (per 1000)	Deaths due to cause (%)	Mortality rate from cause (per 1000)	Efficacy of intervention (%)	Usage of intervention (%)	Implied mortality reduction (per 1000)	Interaction (%)	Efficacy (%)	Not independent (per 1000)
Vitamin A	Various	80	25-35%	20-28	100%	100%	20-28			
	Diarrhea-cofactor			12				50-71	100%	6-9
	Measles-cofactor			4				33-46	100%	1-2
	Total cofactors									8-11
	Remaining Vitamin A Effect						9-21			
Nutrition	Malnutrition	80	35-60%	28-48	20-25%	100%	6-12			
Education	Diarrhea-cofactor			12				61	20-25%	2
	Measles-cofactor			4				45	20-25%	0-1
	Total cofactors									2
	Remaining Nutrition Education Effect						4-10			
Summary ORS/ORT (+ N + A)	Diarrhea						9			
Imm. (+ N + A)	Imm. Diseases						5			
Remaining A	Other						9-21			
Remaining N	Other						4-10			
Total							27-45			

was breastfed as the dependent variable. Columns 1-4 present the coefficient on the *posyandu* treatment dummy as controls are cumulatively added until columns 5-6 which include all individual and time-varying community controls as well as year of birth and location fixed effects.[67] When subdistrict fixed effects are used, the *posyandu* effect on breastfeeding is an additional two months and highly significant, although the effect is only half a month and not significant when village fixed effects are used instead.[68] Again, this result (two months additional breastfeeding when using sub-district fixed effects) is robust to different cohort definitions and varying controls. Once again, it is important to note the error inherent in mothers recalling how long they breastfed for (and it is not recorded whether this was exclusive breastfeeding).

Figure 2.6 displays the *posyandu* effect on breastfeeding duration by relative age. The results suggest that impact of breastfeeding lagged mortality and malnutrition reductions by a couple of years, suggesting that may have taken time for this component of the program to become effective. The two months additional breastfeeding is only an incremental 10 percent duration on average across the sample, probably too low to fully explain by itself the malnutrition and mortality results.

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[67] Individual controls are mother's age at time of child's birth, urban, age of mother at menarche, mother's literacy and education, whether the mother had a pregnancy check-up, birth order of the child, and dummies for the type of birth attendant. Time-varying village controls remain the same as in malnutrition regressions. Household controls are omitted since they are contemporaneous measures of household economic well-being (income, wealth and consumption) rather than at time of birth; results are robust to their inclusion.

[68] Using village fixed effects and including the period of gestation in column 7 results in a statistically significant and very large effect of nine and a half months, but this is restricts us to a much smaller sample and it is unclear why this variable was available only for some children.

However, education on complementary feeding could not be estimated and this aspect would also have been important, as will be the downwards-bias of the measurement error due to recall data. Nonetheless, it is clear that the nutrition education did have an effect on breastfeeding behavior, and this lagged effect may help explain the continued downward trend in the mortality and malnutrition graphs.

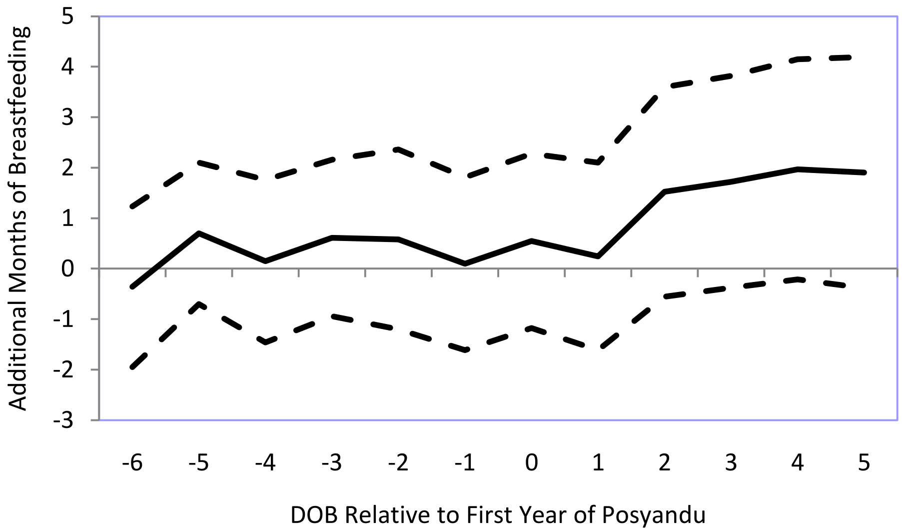
Table 2.6: Increased duration of breastfeeding

Months Breastfed as Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Posyandu effect	0.9*	2.0***	2.1***	2.1***	2.0***	0.5	9.5**
	0.083	*0.004*	*0.002*	*0.002*	*0.003*	*0.340*	*0.042*
Individual controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	No	No	Yes	Yes	Yes	Yes	Yes
Year of birth FE	No	No	No	Yes	Yes	Yes	Yes
Location FE	No	No	No	No	Sub-dist.	Village	Village
Observations	10,563	10,563	10,563	10,563	10,563	10,563	1,589

Notes: individual controls include mother's age at birth, urban, age at menarche, mother's literacy and years of education, pregnancy check-up, birth order, type of birth attendant. Time-varying village controls include whether at time of birth there was a sub-district health center, public transport, piped drinking water. Sample is ever-married women 15-49 years who have ever had children and were between 15 and 40 at time of birth. Errors are clustered at village level. P-values are reported in italics.

With the two components of the *posyandu* likely to reduce malnutrition being growth monitoring and nutrition education (including exclusive breastfeeding) and the use of ORT, these results suggest that the nutrition education was effective and therefore provides support for the efficacy of growth monitoring when combined with effective nutrition advice in reducing malnutrition.

Fig. 2.6. *Posyandu* effect on breastfeeding duration by relative age



Test Scores

With *posyandu* leading to significant reductions in malnutrition, and the known impairment of cognitive development due to malnutrition, we might expect to see reductions in cognitive impairment for children born after a *posyandu* as well. The IFLS data include national test scores for a range of subjects. Table 2.7 Panel A presents the results of regressing normalized test scores for each subject as well as the total over all subjects on a cohort dummy, child and household controls, the number of schools in the community at time of birth, and location and year of birth dummies. Statistical power is a problem since data are available only for children aged 10-14 years in 2000. To increase the sample size, the treatment and control cohorts are taken over a wider age range, with treated children being those born two years before a *posyandu* until five years afterwards, and untreated children being those born four to nine years before a *posyandu*. Moreover, the results presented here use sub-district dummies (errors are clustered at the village-level); results are insignificant when village-level dummies are used.

The coefficient on the cohort dummy, representing the *posyandu* effect, is the number of standard deviations higher the treated cohort scores are on average than untreated. The effects are only significant at 5 or 10 percent levels and only using subdistrict location dummies, so should be treated at best as suggestive evidence only. However, a falsification experiment in Panel B of Table 2.7 similar to that employed with the malnutrition analysis, comparing two treated cohorts, shows no difference in average scores. The results of Panel A and B are thus consistent with the possibility of reduced malnutrition during a child's first two years leading to reduced cognitive impairment, although are not strong evidence of it as such.

If such an effect was true, then the indicated magnitude of effects would be substantial, ranging from 0.24 to 0.37 standard deviations. Table 2.8 summarizes the estimated effects on test scores from other education and health interventions discussed in Section 2.2. The possible *posyandu* effects are of similar magnitude to other health interventions, such as the INCAP program in Guatemala, and towards the higher end of education interventions, such as computer-assisted learning, teacher training and remedial education.[69] However, the costs of health interventions such as these are

[69] The size of *posyandu* effect is lower than education effects from some earlier studies. In a retrospective study on Ghana, Glewwe and Jacoby (1994) found that out of eighteen teacher and school variables, few

generally considerably cheaper than the education interventions, suggesting a higher cost-effectiveness. This is not to say that education interventions should not be pursued, but if the potential *posyandu* effects were accurate, it does support the notion that relatively inexpensive health interventions early on in life can substantially improve human capital development, and, as Heckman argues, *pace* Krueger, are likely to increase the effectiveness of later education interventions.[70]

Having examined the significant reductions in child malnutrition and mortality due to the *posyandu*, as well as possible increases in test scores, the next section turns to the question of how cost-effective the program was.

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had an effect on test scores. They estimated that school facilities had a large impact: repairing leaking classrooms increased reading scores by 2.0 standard deviations and maths scores by 2.2, mainly by reducing school closures due to rain; blackboards increased reading by 1.9 and maths by 1.8, and adding a library increased reading by 0.3 and maths by 1.2, while teaching experience indirectly affected test scores by raising grade attainment. Similarly, Glewwe et al. (1995) examined more than forty teacher and school characteristics and found few significantly associated with test scores; having an effect were eye examinations (0.37 improvement in maths), teacher training within the last three years (0.66 in reading), the use of textbooks in class (0.14 in reading), and the regular testing of students (0.21 in maths, 0.25 in reading). Of the eight teacher and school variables Kingdon (1996) studied in India, only teachers' education (0.13 increase in reading scores per extra year of education) and going from none to complete physical facilities (increasing maths by 0.7 and reading by 1.0) had a significant or substantial impact. However, while some of these are very large effects, as Glewwe and Kremer (2006) discuss, the retrospective nature of the studies means there are potentially a number of biases in the estimates.

[70] It should also be noted that what is being identified here is the long-term effect of a health *policy* on education outcomes, not the effect of health *status* (see Glewwe and Miguel (2008).

Table 2.7. Posyandu effect on test scores

Panel A: Posyandu effect	Moral Educ.	Indonesian	Science	Social Studies	Mathematics	Total Score
Posyandu effect	0.17	0.27*	0.26*	0.37**	0.24*	0.29*
(s.e.)	*(0.14)*	*(0.16)*	*(0.14)*	*(0.16)*	*(0.14)*	*(0.16)*
(p-value)	*(0.23)*	*(0.10)*	*(0.07)*	*(0.02)*	*(0.08)*	*(0.07)*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Community controls	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Sub-dist.	Sub-dist.	Sub-dist.	Sub-dist.	Sub-dist.	Sub-dist.
Observations	542	537	532	533	533	533
R-Squared	0.21	0.26	0.25	0.19	0.27	0.27

Panel B: Falsification experiment	Moral Educ.	Indonesian	Science	Social Studies	Mathematics	Total Score
Posyandu effect	0.03	0.01	-0.03	-0.03	-0.10	-0.01
(s.e.)	*(0.08)*	*(0.08)*	*(0.11)*	*(0.10)*	*(0.08)*	*(0.09)*
(p-value)	*(0.72)*	*(0.95)*	*(0.75)*	*(0.75)*	*(0.22)*	*(0.93)*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Community controls	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Sub-dist.	Sub-dist.	Sub-dist.	Sub-dist.	Sub-dist.	Sub-dist.
Observations	858	848	844	840	845	839
R-Squared	0.20	0.20	0.18	0.14	0.21	0.23

Notes: sample is children aged 10-14 years.
* significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent.
Posyandu effect is coefficient on cohort dummy, which takes 1 if relative age is 2 years before posyandus to 5 years after and 0 if 4-9 years before. Includes sub-district and year of birth dummies. Individual controls are age, age when tested, whether repeated grade, age when began school, sex, urban, head of household's education. Household controls are household wealth and income. Time-varying village controls are number of schools at time of birth.

2.6. Cost-effectiveness

Estimates of the cost of the *posyandu* program vary. Rohde (1993) cites numerous cost studies as finding start-up costs of USD 2-4 per child and recurring annual costs from USD 0.33-0.75 per child, of which 82 percent are expended at the *posyandu*, 17 percent at the sub-district health center and 1 percent at the district level. These costs exclude volunteer time. Mason *et al.* (2006) estimates the costs at USD 2-11 per child per year, although it is unclear to which year's prices these costs refer and thus how to compare them to Rohde's. Mason *et al.* (1999) estimate the costs of such programs internationally in general at USD 5-15 without food supplementation, and twice this amount with food.

Table 2.9 summarizes costs and cost-effectiveness for a range of different interventions in various countries from a number of sources. Care must be taken in comparing these since whether official or PPP exchange rates are used and which year's prices is unclear. Nonetheless, what it is clear is that the costs of the *posyandu* are amongst the lowest of all interventions. Further work is required to calculate the cost-effectiveness of *posyandu* in terms of cost per death saved, per malnourished child averted, and per disability-adjusted life-year (DALY) gained, but Behrman *et al.* (2004) identify breastfeeding promotion, vitamin A supplementation, immunization and ORT as amongst the most cost-effective treatments from a wide summary of the literature. Given these are the main components of the *posyandu*, and the fact the *posyandu* cost

Table 2.8. Comparison of education effects from various interventions

Type of Intervention	Intervention	Country	Best effect on test scores (SD)*	Source
Education (rigorous)	Merit-based scholarships	Kenya	0.12	Kremer et al (2008)
	Test-based teacher bonuses	Kenya	0.14 avg (0.34 high)	Glewwe et al (2008)
	Test-based teacher bonuses	India	0.12-0.19	Muralidharan and Sundararaman (2008)
	Computer-assisted learning	India	0.28	Linden (2008)
	Computer-assisted learning and teacher training program	India	0.25-0.35	He et al (2008)
	Computer-assisted learning	India	0.47	Banerjee et al (2007)
	Remedial education	India	0.28	Banerjee et al (2007)
	Camera-based monitoring	India	0.17-0.21	Duflo et al (2007)
Health	Food supplement (INCAP)	Guatemala	0.25	e.g. Behrman (2008)
	Posyandus	Indonesia	0.24-0.37	Wai-Poi (2008)
Education (less rigorous)	Blackboards	Ghana	1.8-1.9	Glewwe and Jacoby (1994)
	Library	Ghana	0.3-1.2	Glewwe and Jacoby (1994)
	Repairing leaking classrooms	Ghana	2.0-2.2	Glewwe and Jacoby (1994)
	Eye examinations	Jamaica	0.37	Glewwe, Grosh, Jacoby and Lockheed (1995)
	Teacher training	Jamaica	0.66	Glewwe, Grosh, Jacoby and Lockheed (1995)
	Use of textbooks in class	Jamaica	0.14	Glewwe, Grosh, Jacoby and Lockheed (1995)
	Regular testing of students	Jamaica	0.21-0.25	Glewwe, Grosh, Jacoby and Lockheed (1995)
	Extra year of teacher education	India	0.13	Kingdon (1996)
	Complete addition of physical facilities	India	0.7-1.0	Kingdon (1996)

Notes: In cases where there were differential effects on test scores due to different treatments, the highest effect has been stated. That is, this effect was not necessarily seen for all students or all treatments.

per child is one of the lowest per child on cost alone in the literature, it seems very likely that the *posyandu* have one of the highest cost-effectiveness ratios of any child primary health-care intervention. The cost-effectiveness of the *posyandu* is in part due to not being a food supplementation program, but limiting itself to growth promotion (growth monitoring and nutrition advice). The provision of supplementary foods was deemed the least cost-effective of eight possible strategies for achieving Millennium Development Goal 4 (Edejer *et al.* 2005); see also Horton *et al*. (2004) and Behrman *et al*. (2004). Finally, as Horton *et al.* (2008) observe, the cost-effectiveness of community-based nutrition programs would be increased if the potential cognitive benefits of better nutrition were also achieved, which seems quite possible on the evidence presented in the previous section.

2.7. Further Research and Conclusions

This chapter has used household-level data and a careful empirical approach to demonstrate the success of a large-scale multiple intervention child primary health care program. The results indicate Indonesia's *posyandu* program reduced the chance of an infant dying before one year of age by 2.6 percent, which would account for 36 percent of the fall in infant mortality in Indonesia between 1980 to 1987; similarly the chance of a child dying before five was reduced by 3.6 percent, or 39 percent of the decline in under-five mortality over the same period. While the contribution of different *posyandu* interventions to this reduction cannot be disentangled, the total impact is

Table 2.9. Cost comparisons and cost-effectiveness

Intervention	Source	Year	Country	Costs (USD) Per child or outcome	Per life saved	Per DALY gained	Benefit : Cost
Supplementation and Fortification							
	Allen and Gillespie 2001	2001	Non-specific	1.70 per pregnancy	800		
	Baltussen et al. 2004**	2004		10-50 per person per year		66-115	
Iron supplementation of pregnant women	Behrman et al. 2004	2004	Non-specific	10-13 per woman			6:1 - 14:1
Iron supplementation	Institute of Medicine 1998*, World Bank 1994*	1994	Non-specific	3.17-5.30 per child			
	Allen and Gillespie 2001	2001	Non-specific	0.09	2,000		
	World Bank 1994*	1994	India	0.12 per child			
Iron fortification	World Bank 1994*	1994	Guatemala	0.20-1.00 per child			
	World Bank 1994*			0.09 per child	2,000	66-70	
	Horton and Ross 2003**	2008		0.10-0.12 per person per year			7.8:1
Iron home fortification	Sharieff et al. 2006**	2006		1.20 per person per four months			37:1
Iodine supplementation (reproductive age only)	Allen and Gillespie 2001	2001	Non-specific	0.50 per woman	1,250		
	Behrman et al. 2004	2004	Non-specific	0.25 - 5.0 per woman			15:1 - 520:1
Iodine supplementation (all)	Allen and Gillespie 2001	2001	Non-specific	0.50	4,650		

Table 2.9. Continued

Iodine oil injection	Institute of Medicine 1998*, World Bank 1994*	1994	Peru	2.75 per child			
	Institute of Medicine 1998*, World Bank 1994*	1994	Zaire	0.80 per child			
	Institute of Medicine 1998*, World Bank 1994*	1994	Non-specific	1.25 per child			
Iodine fortification	Allen and Gillespie 2001	2001	Non-specific	0.05	1,000		
	Institute of Medicine 1998*, World Bank 1994*	1994	Indonesia	0.05 per child			
	Institute of Medicine 1998*, World Bank 1994*	1994	Italy	0.02-0.05 per child	1,000	34-36	
	Institute of Medicine 1998*, World Bank 1994*	1994	India	0.05 per child			
	Horton et al. 2008	2008		0.05 per child			30:1
Vitamin A supplementation of under fives	Allen and Gillespie 2001	2001	Non-specific	0.20	325		
	Rassas et al. 2004a*	2004	Ghana	0.90 per child	277	11	
	Rassas et al. 2004b*	2004	Zambia	1.23 per child	162	6-7	
	Fiedler 2000*	2000	Nepal	1.25 per child	327	11-12	
	Chung et al. 2000**, Fiedler 2000**, Horton 1999**		Non-specific	0.20 per person per year		3-16	
	Behrman et al. 2004	2004	Non-specific	1-10 per child			4.3:1 - 43:1
Vitamin A fortification	Allen and Gillespie 2001	2001	Non-specific	0.05-0.15	1,000		
	Institute of Medicine 1998*		Guatemala	0.17 per child	1,000	33-35	
	World Bank 1994*		Non-specific	0.05-0.15 per child			

Table 2.9. Continued

Zinc supplementation	Robberstad et al. 2004*	2004	Non-specific	0.47 per child	2,100	73	
Zinc home fortification	Sharieff et al. 2006**	2006		1.20 per person per four months		12	
Folate fortification	Grosse et al. 2005**	2005	USA	0.01 per person per year			12:1 to 39:1
Biofortification (vitamin A and iron)	Meenakshi et al. 2007**	2007		0.5-1.0m per country per year		10-120	4:1 to 50:1
	Behrman et al. 2004	2004	Non-specific				8:1 - 19:1
Nutrition Education							
Nutrition education	Allen and Gillespie 2001	2001	Non-specific	5.00	238		
	Mason et al. 1999**, World Bank 2006**		Non-specific	5-10 no food			
	Mason et al. 1999**, World Bank 2006**		Non-specific	10-20 with food			
	Ho 1985**		Tamil Nadu			53	
	Mason et al. 2006		Tamil Nadu	9 per child per year + 3 with food			
	Fiedler 2007**		India			39	
	Waters et al 2006**		Peru			61-153	
	Mason et al. 2006		Costa Rica	12.5 per child per year with food			
Breastfeeding support	Horton et al. 1996*	1996	Brazil, Honduras, Mexico	0.30-0.40 per birth, 0.65-1.10 per diarrhea case averted	100-200	3-7	

Table 2.9. Continued

Breastfeeding promotion	Ross et al. 1987*	1987	Mali	2-3 per child	282	11	
	Chee et al 2002*	2002	Ghana	16 per child, 5-58 per adopter of exclusive breastfeeding	203	8	
	Chee et al 2003*	2003	Madagascar	4.41 per child, 10-17 per adopter of exclusive breastfeeding			
	Horton et al. 1996**	1996		0.30-0.40 per birth		2-4	
Breastfeeding promotion (hospital)	Horton et al. 1996**	1996		3-4 per birth		12-19	
	Behrman et al. 2004	2004	Non-specific	133-1,064 per outcome			4.80:1 - 7.35:1
Nutrition programs - less intensive	Caulfield et al. 2006	2006	Non-specific	2-5 per child			
Nutrition programs - more intensive	Caulfield et al. 2006	2006	Non-specific	5-10 per child			
Supplementary feeding programme	Mason et al. 2006	1980s	Zimbabwe	50 per child per year			
Growth monitoring and counseling	Fiedler 2003*	2003	Honduras	4 per child, 20 per nudernourished child averted	240-320	8-11	
	Ashworth et al. 2008		Honduras	6.84 per child (4.00 per child variable)			

Table 2.9. Continued

Worming					
School age	Miguel and Kremer 2004**	2004		0.49 per person per year	3:1 to 60:1
	Fiedler 2007**	2007		0.32 per person per year	
Preschoolers	Horton et al. 2008	2008		0.50 per person per year	6:1
Integrated Programs					
Intensive pre-school program with considerable nutrition for poor families	Behrman et al. 2004	2004	Non-specific		1.4:1 - 2.9:1

Table 2.9. Continued

	Ross 1997*, WHO 2002*	1997	Various	76-101 per undernourished child averted	1,200	41-43	
	Behrman et al. 2004	2004	Non-specific	40 per child			9.4:1 - 16.2:1
Child survival program with nutrution component	Mason et al. 2006	1980s	Tanzania (Iringa)	8-17 per child per year			
	Mason et al. 2006		Tanzania	2-3 per child per year			
	Mason et al. 2006		Bangladesh (BINP)	18 per child per year			
	Mason et al. 2006	1970s-1980s	Thailand	11 per child per year			
	Rohde 1993	**1980s-1990s**	**Indonesia**	**0.33-0.75 per child per year with 2-4 per child start-up costs**			
	Mason et al. 2006	**1980s-1990s**	**Indonesia**	**2-11 per child per year**			

Notes: * From Caulfield et al. 2006; ** From Horton et al. 2008.

consistent with aggregating the individual intervention effects which are known in the literature. Moreover, children were 19 to 25 percent less likely to be stunted or underweight, which comes from a combination of growth monitoring and nutrition intervention and ORT. Consistent with the known effects of infant and child malnutrition on cognitive development, there is also evidence that the program had a significant effect on test scores, to the order of a 0.22 to 0.35 standard deviation improvement in test scores.

There is considerable scope for further research; three key areas are discussed here. First, using the program impact on mortality and malnutrition, a more detailed cost benefit analysis is required. While a survey of the literature shows the *posyandu* costs to be low by contrast with other health interventions, suggesting that its cost-effectiveness is amongst the highest given the significant reductions in malnutrition and mortality, the cost per DALY saved needs to be calculated to facilitate a proper comparison. Moreover, the costs of each intervention in the program are well known; if the individual intervention effects under the program could be disentangled, a more sophisticated cost-effectiveness analysis would be possible. The current data and research design do not allow such a decomposition in a rigorous manner. However, as Caulfield *et al.* (2006) observe "consensus is growing on the need to evaluate a package of services rather than use complex strategies to tease apart the effects of specific program elements." Similarly, it is important to note how affordable the *posyandu* program is. From a policy perspective, given the low cost, it is the reduced-form result on infant and child mortality and health which we are most interested in; the program is cheap enough to replicate in full elsewhere without worrying about which interventions to retain and which to drop.

Given the difficulties scaling such programs up historically, the second area for further research is why it was so successful in Indonesia, yet has so often been ineffective elsewhere. While it is beyond the scope of this chapter to examine in detail, some initial observations can be made. The Indonesian Ministry of Health cites three factors allowing the rapid expansion of the *posyandu*: (i) a high level of political support and commitment at presidential and cabinet level; (ii) the program had already been extensively piloted by government and international organizations; and (iii) a traditional village custom of *gotong-royong*, or mutual self-help centering on the joint responsibility and mutual cooperation of the whole community to each of its members (MOH 1994). The Ministry also notes how linkages with local organizations such as PKK (the village women's organization), village leaders and volunteers strengthened community involvement. This official account is supported by a number of independent commentators, who emphasize the strategy of inducing behavioral change (Rohde and Hendrata 1983; Sanders 1999), the volunteer nature of the *posyandu* and the involvement of the PKK (Sanders 1999; Mason *et al.* 2006)) and the high degree of community participation and self-reliance, which was maintained by the small unit of operation (Rohde and Hendrata 1983; Rohde 1993; Sanders 1999; Mason 2002); a sustained commitment for improving child nutrition and health since the 1970s, both politically and from international agencies (Rohde 1993); and the high capacity of the coordinating unit, BKKBN (National Family Planning Board) (Rohde and Hendrata 1983; Hull and Hull 2005). Many of these same aspects are emphasized as common success factors for similar national-scale programs in countries such as Thailand, Costa Rica, and Tanzania: a focus on fostering behavior change (Mason *et al.* 2006), implementing a range of effective interventions (Mason 2002; Bryce *et al.* 2008), a combination of community-based activities (Mason *et al.* 1999; Allen and Gillespie 2001; Mason 2002; Mason *et al.* 2006) with strong support from central government with powerful champions (Mason *et al.* 1999; Allen and Gillespie 2001; Mason *et al.* 2006; Gillespie *et al.* 2007; Bryce *et al.* 2008), a high ratio of local workers to families so that individual contact can begin to solve problems (Mason *et al.* 1999; Mason *et al.* 2006)[71], and a cultural emphasis on social interconnectedness (Allen and Gillespie 2001; Mason 2002). They are not primarily dependent on poverty reduction (Mason *et al.* 1999). Mason *et al.* (2006) also emphasize the additional contextual factors of women's status and education, lack of social exclusion, and literacy.

The highly localized nature of the *posyandu*, with at least one in every village is also likely to be important in increasing attendance and participation. Duflo (2006) discusses an experiment in India by Banerjee *et al.* (2004), in which a baseline 45 percent absenteeism from child immunization services contributed to a 1 percent fully

[71] Mason *et al.* (1999) note that the two of the largest and most successful such programs were Thailand and Indonesia, which had similar rates of village health workers in proportion to the population, around 1 percent. The Department of Health (1994) confirms this ratio in Indonesia.

immunized rate by two years old. When regular monthly camps were set up in villages to take away travel costs, 22 percent of treatment infants had the appropriate immunization, compared to just 4 percent in control villages. In 40 percent of treatment villages a small gift of food was made as an added incentive. This is similar to the *posyandu* context of regular monthly locations with limited travel and the provision of a free demonstration meal.

Finally, this chapter has studied only the effects on infants and children, due to data availability. However, given the magnitude of improvement in nutrition status while young, as well as the possible large increases in test scores, we might well expect significant effects on outcomes later in life, such as final educational attainment, income and earnings, adult health, such as morbidity, mortality and maternal mortality, and potentially an intergenerational transmission of effects due to improved maternal health and height, and possibly education. The data used in this chapter were collected in 2000. The fourth wave of the IFLS was in the field in 2007 and is at the time of writing currently in the process of being made publically available. This new survey will allow research into the long-term *posyandu* impact on education, income, adult health and intergenerational effects; the program's achievements over the full life-cycle of children who benefited may be both greater and more persistent than identified in this chapter.

Chapter Three: Household Economic Well-being: Concepts and Measurement with Asset Indices[72]

3.1. Introduction

When monetary data for income, wealth or consumption are not available, as is often the case in developing countries, it has become increasingly popular to use an index constructed from variables on asset ownership as a measure of household economic well-being. There is now a considerable literature using such indices and they are becoming widely used in development studies and policy. However, what is essentially the *same* index is often used to represent *different* aspects of household well-being, such as living standards or wealth. Moreover, while a number of papers evaluate their index, often by comparing its predictive power for a particular socio-economic outcome against household expenditure, no paper that I am aware of has systematically examined as full a range of current constructions (choice of variables and weights) or compared them to monetary measures. The main contributions are to provide a summary of the current use of asset measures, a systematic evaluation of indices constructed from different approaches, and to make practical recommendations with

[72] This chapter was developed under the guidance of Sy Spilerman and Florencia Torche at the Center for Wealth and Inequality at Columbia University, to whom many thanks are owed. It has also benefited greatly from comments from seminar participants at SMERU in Indonesia and discussions with members of the IGERT International Development and Globalization Program at Columbia University, particularly Gabriella Carolini, Dan Choate, Ashley Fox, Dan Neilson and Cuz Potter. Thanks are due to Emmanuela Gakidou and Diana Lee for their assistance in implementing the DiHOPIT estimator.

respect to survey design given specific research objectives, while outlining the most important directions for future research.

This chapter address five issues. First, while research in the developed world has revealed the different roles played by household wealth, income, consumption, and living standards, as factors in the welfare of families (for example, Behrman *et. al.* 1995; Mayer 1997), these concepts tend to be conflated in studies of developing countries. The distinctions between these components of what, more generally, we might call 'economic well-being', are important because they can have very different effects on disparate aspects of life outcomes that are of interest to researchers. For example, wealth holdings can enable a household to weather economic shocks such as from illness or unemployment and thereby keep a child in school, but household income may be a better predictor of health status. Similarly, household wealth is a better indicator of what income will be after retirement than current income. Thus, as researchers proceed to address questions of population well-being in developing countries, it is critical that they be able to accurately assess the relationship between the components of household resources and the various life course outcomes. As a first issue I address the distinctions between these concepts.

In developing countries it is difficult to collect monetary data on household wealth, and even on income. Many of these countries are not fully monetarized and, at least partially, use a barter economy. Data on earnings and income are collected in some household surveys, but information on household wealth is rarely available. However, data on ownership of a range of household items are frequently collected. For this reason researchers have been exploring strategies for using asset data to proxy the economic well-being of households in developing countries. The various studies that have been carried out differ in methodological approach for converting asset holdings into indices and, more seriously, they differ in regard to what the indices purportedly measure. Thus, Filmer and Pritchett (1999, 2001) claim that their index captures household wealth, McKenzie (2005) speaks of living standards, Ferguson *et al.* (2003) of permanent income, Burger *et al.* (2006) of marketable wealth, Sahn and Stifel (2003) of well-being, and Booysen *et al.* (2005) of poverty. However, the asset items used by these authors are quite similar, and their weighting methodologies generally differ only modestly. In short, it is not apparent that these studies are measuring different constructs, rather than applying different names to similar indices. But since the various components of economic well-being may have different effects on outcome variables of interest, it is rather consequential that indices be formulated that predict validly to a particular monetary measure. Thus, as a second issue I examine what is actually measured by the different indices that have been constructed.

A third question addressed concerns the sensitivity of results to index construction strategy, especially to choice of weights and selection of the underlying variables. Existing approaches differ in which asset variables they incorporate and how they weight them. The most common weighting has been derived from principal component analysis (see Filmer and Pritchett, 1999, 2001; McKenzie, 2005). We also look in detail at factor analysis (Sahn and Stifel 2003a, 2003b), multiple correspondence analysis (Booysen *et al.* 2005; Burger *et al.* 2006), and a hierarchical ordered probit model (Ferguson *et al.* 2003).[73] These are competing approaches for solving the same general problem. Does one method dominate another in general or, perhaps, for specific kinds of problems? I also examine a range of different variable formulations (and aggregations) to see how significant this choice is. Is more better, or can a well-selected parsimonious index act as well as one with a larger variable base? Are different variable classes better indicators of different aspects of economic well-being? Proper construction of these indices is important given their increasingly wide use in policy. Many development programmes are targeted at poor households, villages or regions. Successful targeting relies upon the ability to identify in-need recipients.[74]

An application of these indices in research is as a proxy for some component of a household's economic status. I compare the results of regressions using monetary

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[73] A distinct approach is to regress consumption on the household variables and controls and use the household coefficients as weights for those variables in constructing an asset index, as used in, for example, Nicaragua (IFPRI) and Grosh and Baker (1995). This obviously requires that reliable household consumption data are available originally, one of the restrictions that asset indices are often employed to overcome, and as such is not considered here. See Castaneda and Lindert (2005) for more detail.

[74] For example, a 'Wealth Index' is included in the widely used Demographic and Health Survey data. Mexico's well-known Oportunidades (previously PROGRESA) program uses an asset index approach to target poor households (see Skoufias *et al.* (1999)). They are also used in Chile (Ficha CAS), Costa Rica (SIPO), Columbia (SISBEN's PRINQUAL procedure); see Castaneda and Lindert (2005). In the Indonesian context, which the empirical section of this chapter focuses on, such indices are currently being used to target a variety of cash transfers and non-cash benefits.

measures, the index proxies, or no economic measure, to understand what potential biases are introduced by the use of an asset index as an explanatory variable.

Finally, I ask whether there are conceptual shortcomings associated with this whole class of formulations. One such issue may be that they all produce a one-dimensional construct. Researchers might be interested in not only aggregate economic well-being, but also its components separately (Deaton (1997) suggests that it may be better to keep them separate); a one-dimensional index does not capture this. With this in mind the possibility of multidimensional indices is introduced. One such approach is to retain multiple dimensions often available from the current weighting methodologies. Another is to construct two different indices from different underlying variables. For example, we could ask a battery of questions about valuable 'stock' holdings, such as indicators on bank accounts, stocks, bonds, home-ownership, real estate, cars, livestock – that is, items in which wealth is stored may be indicators of economic security – and then another set of questions which reflect daily living standards. But should these two sets of items be analyzed together, seeking a two-dimensional solution, or separately, seeking two one-factor solutions?

At the end of the chapter, I recommend approaches for different research objectives: which variables are best for different aspects of economic well-being when designing a study or when the available items are sufficient to permit a selection among them, and which of the index construction methodologies is most appropriate. The optimal choice will vary in different contexts and for different purposes. For example, depending on the range of the economic distribution we are targeting, we may want items that would permit distinguishing among poor families or only among wealthy families.

The chapter is organized as follows. The following section discusses conceptual issues regarding the nature of economic well-being and what one might want to measure. Section 3.3 summarizes the different weighting methodologies commonly used in the literature, as well as introducing potential modifications and extensions of the methodology. The empirical section of the chapter begins with Section 3.4, introducing the Indonesian Family Life Survey data used in the analysis, and examining how well asset indices proxy for different monetary measures and how sensitive the results are to different index construction. Section 3.5 quantifies the potential research bias of using or omitting such indices, while Section 3.6 concludes with recommendations for index construction given different research or policy goals and suggestions for future household survey design.

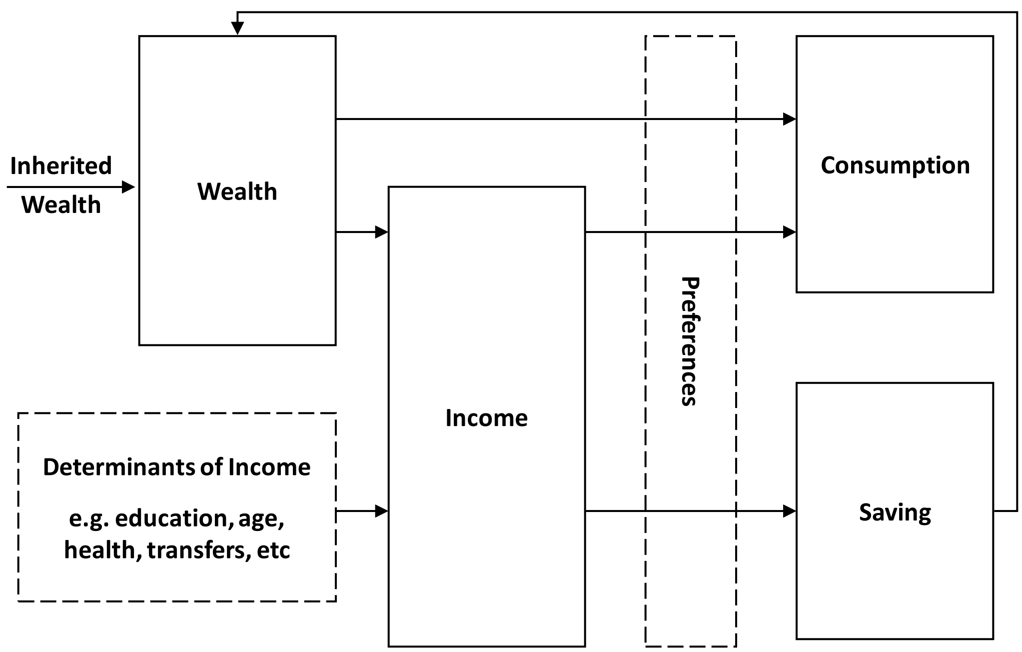
3.2. Distinctions Between Components of Economic Well-being

Already noted are the variety of terms used, such as wealth, economic status, living standards, income, permanent income, marketable wealth, and welfare and well-being, that asset indices have been claimed to represent. Yet while related, many of these concepts are clearly distinct from each other, in the abstract and in economic implication. Thus it is important to address what conceptual differences exist between these notions and how they relate to the standard monetary measures of income, wealth and consumption. First I suggest that there are three classes of concepts here: unmeasurables, such as economic security; measurables in principle, which are often difficult to measure in reality, such as wealth; and measurables in practice, such as the type of toilet a household uses or the quality of building materials. In this section we distinguish amongst unmeasurables, which are more conceptual in nature, and examine their relationship with measurables in principle. The empirical part of the chapter examines the relationship between the measurables in principle and those in practice.

Consider income, wealth and consumption, all measurable in principle. Income is treated here as including all cash and non-cash earnings from labor, businesses or investments. Consumption similarly includes both expenditure and consumed self-production and non-monetary remuneration. Wealth is taken as the aggregate value of all household assets and holdings, whether physical valuables, financial assets, or business assets. The distinction between durables (wealth) and non-durables (consumption) differs between and within countries, and evolves over time. For example, a radio might be considered consumption in a richer country, but a store of wealth in a poorer one.

Income, wealth and consumption characterize interdependent economic flows, as shown in Figure 3.1. Two points are salient. First, income and wealth are both determinants of consumption. Second, there is a considerable degree of endogeneity in the system. Wealth not only indirectly drives consumption through the income it can produce, such as rents and interest, but also directly; wealth can be sold or borrowed against to fund consumption in times of low income. However, wealth itself is also determined by the choice over time to consume or save income (which may be from labor earnings).

Fig. 3.1. Relationship between income, wealth and consumption



In addition, income and consumption are flows, whereas wealth is a stock. The stock of wealth can be considered as a series of future consumption flows. Two households enjoying the same levels of both consumption and income might have considerably different stocks of wealth. While this means that both households enjoy the same level of material comforts,[75] the wealthier household is in a better position to weather under- or unemployment, illness, natural disaster or some other shock, by either selling off wealth or using it as collateral for loans, thus smoothing consumption.[76] Furthermore, the stock of wealth represents future consumption flows that can be passed on to one's children.

Now consider the relationship of income, wealth and consumption with the more abstract terms in the literature on asset indices, which are not directly measurable, such as living standards, permanent income, economic status, economic well-being, and economic welfare. Definitions are somewhat arbitrary; the goal here is not semantic but to highlight conceptual differences. I begin with *living standards*, the most immediate, which I associate with levels of daily material comfort. Considered broadly, it can encompass not only housing, food, clothing, utilities and transportation, but also such aspects as neighborhood and environmental quality. Living standards most directly corresponds to consumption; many of the less directly consumed material comforts such as environmental quality are indirectly consumed through location of dwelling, and constitute part of a household's rent (or rental income foregone in the case of

[75] Assuming consumption is adjusted to include the opportunity cost of rent forgone implicit in home-ownership and other significant durables

[76] A household's ability to borrow does not depend solely on wealth; access to micro-credit or revolving community funds (such as the *Arisan* in Indonesia) may depend more on the household's standing in the community.

homeowners).[77] Deaton and Grosh (2000:95) argue consumption is "the best measure of the economic concept of living standards", a view shared by many (McKenzie 2005).[78]

The second notion I consider is *economic security*, which indicates how safe or vulnerable current living standards are. Economic security is determined by two factors. The first is the vulnerability of sources of income, which fund living standards. Permanent workers with salaries have more secure incomes than temporary and piecemeal-wage workers. Developing country incomes often fluctuate, particularly for those in the agricultural sector facing the risk of droughts, floods, crop failures and variable prices. The second factor of economic security is the extent of recourses available to a household if income is disrupted. A higher degree of economic security enables households to maintain more constant living standards even as incomes fluctuate. Households whose consumption is driven by current income may find themselves at or below subsistence levels during periods of difficulty. To avoid such situations, households can try smoothing consumption, saving income during good times and consuming at levels greater than current income during bad by dipping into savings. Households without economic security are unable to do this.

[77] Of course, not all enjoyment of government and non-government services can be linked to location and other household expenditure. Moreover, living standards also include wealth items, such as paintings. Thus living standards are not strictly the same as consumption.

[78] Deaton (1997:148-149) also argues measuring consumption is more practical than income in developing countries.

This distinction between current living standards and their sustainability, along with the ability to smooth consumption, led Friedman (1957) to theorize that consumption was determined not by current income but by permanent income, a concept established over a much longer period than annual income (perhaps over a lifetime), and thus much less volatile.[79] Indeed, Ferguson *et al.* (2003) use their index as a proxy for permanent income. Bollen *et al.* (2002) use the terms economic status and permanent income to describe what their index measures, emphasizing that "economic status tends to have a less transitory significance than other aspects of income or gain in resources", much like permanent income. Filmer and Pritchett (2001), in their influential paper estimating 'wealth effects' on educational enrolments in India, use their index as a measure of wealth, which they in turn see as a proxy for long-run economic status. In particular, they "are not proposing this household index as a measure of *current* welfare or poverty" (p.116, my emphasis), but see educational enrolment as depending on long-run as well as current expenditures. Thus, at least in this respect, they conceive of economic status similarly to Bollen *et al*.[80]

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[79] See Deaton (1997) for a discussion of the theory of, and evidence for, permanent income.

[80] Booysen *et al.* (2005) use an household index to study trends in poverty (and inequality) in Africa. They note that "in essence, one can distinguish between the conventional approach to the measurement of poverty and inequality, which is money-metric and uses income and/or expenditure data, and a number of alternative approaches, such as those for instance which employ various other socio-economic indicators to measure poverty and inequality." However, Filmer and Pritchett (2001:fn.1) argue that the household index is a poor measure of poverty, since "the conventional notion of poverty is based on the *flow* of consumption relative to some pre-determined threshold, whereas, by aggregating assets, I am establishing only a measure of a stock. Second, the categorization used is based on a relative measure (that is, the household's ranking within the distribution), whereas poverty thresholds typically are based on the expenditure necessary for the consumption of a determined bundle of goods." Thus it is important

A third notion, *economic well-being*, combines current levels of material comfort (static in perspective) with some sense of economic security (dynamic in perspective). This is similar to the manner in which economic status is often used in the literature, combining a longer time horizon and consideration of both stock and flow. We can consider economic well-being a broader concept taking into account both living standards (strongly linked to consumption) and economic security (determined in part by wealth), although it is important to also consider the role of income. Consumption is generally afforded out of income, and non-consumed income becomes saved wealth in the future. So income is an important determinant of both aspects of economic well-being.

Thus I note two distinct concepts, neither of which is directly measurable. The first, living standards, represents current levels of material comfort and amenities, and would include nutrition, transportation, neighborhood amenities and environmental quality. This most directly corresponds to consumption in monetary terms with the caveats previously discussed. The second, economic security, represents the security and stability of these living standards over time. This depends on the sources of income and its ability to withstand unexpected shocks in income, the latter largely dependant on its ability to borrow or raise money and so partly determined by wealth. At a more general

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to define what is meant by poverty. It is often used to mean an individual or household with daily consumption under a certain level (one and two dollars a day are commonly used), which is an absolute flow measure. However, poverty is also used sometimes in a more general sense to mean households that are poor relative to others in the country or region. In this sense it is a relative measure, which might be either a stock, a flow, or both. More generally, see Hulme and McKay (2005) on the multidimensional nature of poverty and the need to move beyond monetary measures.

level, both current levels of living standards and their sustainability combine to reflect a household's economic well-being. While the nature of the asset and other household characteristics used to construct asset indices are clearly associated with each of these concepts, the literature has used essentially the same index to represent all three, which I have argued to be related but distinct.[81] Admittedly, there is threshold effect which influences how sharp these conceptual differences are in reality. At extreme levels of deprivation, living standards, economic security and quality of life are all very closely tied to consumption, (generally the same as income in these cases, with wealth being negligible). However, as income (and so wealth and consumption) increases, the differences discussed become more manifest.

Thus consumption, income and wealth are important but distinct indicators of economic well-being. This leads us to ask what the asset indices constructed in the literature actually measure? Should we use a single index measure, or do we need a multidimensional approach? To address these questions we must first examine how such indices can be constructed.

3.3. Methodological Approaches to the Construction of Asset Indices

[81] Of course, given a sufficient range of items, in principle we could construct an index related to quality of life; indeed, the Human Development Index (HDI), a comparative measure of income, literacy, education and life expectancy used by the UN, is one such measure. However, as Deaton observes, "while it is possible to consider methods for combining these indicators into a single measure, there is no adequate theory underlying such an aggregate so that weighting schemes are inevitably arbitrary, and it is more informative – as well as honest – to keep the different indicators separate." (1997:149.)

Constructing an asset index is conceptually simple. A range of household indicators, drawn from easily observable or verifiable variables on asset ownership, housing, water and sanitation quality, and household characteristics, are linearly weighted to give a score for each household. Two main methodological questions arise: (i) which variables should be included? (ii) how should they be weighted? The latter question has received more focus in the literature than the former, perhaps because researchers' choice of variables is often determined more by availability in existing datasets than theoretical considerations. I consider both sets of options in this section.

3.3.1 Selection of household variables

There is a wide range of possible household characteristics that could be included in an index. Typically indices will include a number of asset ownership indicators, such as bicycles, motorbikes and cars, TVs, fridges and other household appliances; basic housing quality variables, such as quality of building materials, electricity and number of rooms; and water and sanitation variables such as source of drinking and washing water, garbage collection, type of toilet and method of sewage disposal. Some researchers also include demographics characteristics such as number in household, as well as head of household covariates, like age, education and employment status. In addition, we might also include household social benefits such as access to subsidized health care or education services, or participation in insurance or credit schemes. Here we consider the question of which variables to use.

One issue is whether the distinction between measures and determinants of economic well-being is important. For example, a head of household covariate such as education is known to be a *determinant* of household income, whereas cooking with biomass versus kerosene is a *measure* of income (or consumption). Moreover, often researchers will want to exclude head of household covariates, as they may look to identify the effects of such explanatory variables on the dependent variable independently from that of the asset index.

A related question is whether is it important to distinguish between potential *measures* of wealth, such as having garbage collection, and *stores* of wealth, such as jewelry or savings. A measure of wealth is an indicator that a household is above a certain wealth threshold, but not necessarily where wealth is itself stored. This distinction will depend in part on which component of economic well-being is being approximated. A store of wealth is *a priori* a good indicator of economic security, since it can be used to weather shocks. Whether it is also an indicator of daily living standards will depend on the nature of the asset; durable assets such as fridges and TVs may not only be stores of wealth but also contribute directly to quality of life, whereas an asset like savings does not. Conversely, garbage collection may be a good indicator of living standards or consumption but may not speak to wealth. In practice, indices have included a mix of assets and other household characteristics. This may be appropriate if we wish to approximate daily living standards, but may not be the best formulation to measure wealth. In the next section I examine whether an index constructed strictly from asset ownership, a true asset index, performs better as a measure of wealth.

It is also important that an asset variable does not contain items of very different value. For example, a 'vehicle' variable is problematic, as owning a bicycle is not equal to owning a car. Such variables should be broken down into more narrow categories, such as bicycle, motorbike, car and truck ownership, although some variation will still exist within these new categories. Similarly, 'appliances' is not a useful category; a radio is not commensurable with a television.

Often an index is meant to discriminate over the entire economic distribution. However, when an index is being used to target a particular sub-segment of the population, such as the rich or poor, there is a further consideration in variable choice: variables distinguishing the target population need to be included. An index constructed solely of poverty or middle class indicators will leave the rich clustered around a small range of index values, as most will have, for example, toilets with septic tanks, piped or pumped drinking water, electricity, a television and fridge. However, inclusion of variables such as broadband internet access may lead to better separation; an example of this is shown later in the chapter. Furthermore, variables that might distinguish those on the margins of the target population would be critical in minimizing exclusion of target and inclusion of non-target households. This could be particularly important in the case of poverty-targeting programmes, where improper exclusion could result in significant welfare loss and improper inclusion in substantially higher implementation costs.

Finally, while indicators of household wealth have been discussed, an element of economic security relating households to income shocks which has been neglected in the literature is the likelihood of such shocks in the first place. Although not examined empirically here, researchers and policy makers interested in household economic security should also consider using variables which speak to the vulnerability of income, such as whether a household's income is predominantly agricultural, and whether labour incomes are from permanent or temporary work.

3.3.2 Choice of weights

I now turn to the different approaches currently employed in the literature. The alternative weighting approaches are employed in the absence of detailed household survey consumption data with which to derive indicators weights from a consumption regression (see Casteneda and Lindert 2005 for further on this approach), but generally lack adequate grounding in economic theory, and are somewhat arbitrary. An obvious way to construct an index from the indicator variables is simply to sum them. Although household consumption increases with such an index (Montgomery *et al.* 2000), the problem with an unweighted index is that it seems unlikely that all of the indicator variables should be treated equally. One resolution has been to use prices to weight each indicator. However, collecting such data is costly and often not done in many developing country surveys. In addition, there is enormous variation in the price of some items, such as houses. I concentrate on non-price-weighted indices, reviewing indices created using weights from principal component analysis, principal factor analysis, multiple correspondence analysis, and a hierarchical ordered probit model.

Principal Component Analysis

The most common weighting approach is principal component analysis (PCA), a method popularized in the asset index literature by Filmer and Pritchett (1999, 2001). PCA is a general technique used to reduce a large number of variables, and is discussed in many texts; a full treatment is given in Jolliffe (2004) and Stevens (2002). In essence, PCA reduces the dimensionality of a data set with a large number of interrelated variables, while retaining as much variation as possible, by transforming to a new set of variables, the principal components, ordered so that the first *few* retain most of the variation present in *all* of the original variables (Joliffe, 2004).

In practice this means calculating household scores from a linear weighting of the variables (the weights being the solution to an eigenvalue-eigenvector problem for a positive-semidefinite symmetric matrix), and identifying which combination of weights gives scores explaining the most variation in the variables' variance-covariance matrix. This score for each household, the first principal component, is retained and the process repeated, looking this time for the household scores which explain the most of the remaining variation. The result is the second principal component; further principal components are calculated until all of the variation in the original household variables is explained.

The current practice is to retain the first principal component as the asset index. Filmer and Pritchett (2001) construct such an index in India and estimate the relationship between this proxy for household wealth and children's school enrolment, and to examine the effect of household wealth on educational attainment in 35 developing countries (Filmer and Pritchett 1999). Other papers use a PCA-based index constructed from Demographic and Health Survey data to study health outcomes, such as child mortality (Bonilla-Chacin and Hammer 1999), child survival (Stecklov *et al.*1999), and a variety of others (Gwatkin *et al.* 2000), while Sahn and Stifel (2003a) study poverty. McKenzie (2005) extends the methodology from examining *level* effects to examining *distributional* effects, proposing a relative inequality measure derived from the asset index.

PCA is the most well-known and used weighting method in practice. An appeal of PCA is that it is easily implemented. In addition, it is exploratory by nature and makes no assumptions about the underlying relationship between the variables. However, it does make continuous, multivariate normality distributional assumptions about the variables, which are clearly invalid for dichotomous and categorical variables.

A recent innovation is polychoric PCA (Kolenikov and Angeles 2004), applied by Moser and Felton (2007) to an Ecuadorian dataset. Polychoric PCA draws on the maximum likelihood estimates of correlation between the unobserved normally distributed continuous index variables underlying their discrete ones. They argue one advantage is that it preserves ordinal information of categorical variables, which is lost by simply converting these to mutually exclusive dummies, as some researchers do, although ordinal variables can enter normal PCA directly, (and I later explore the use of cascading dichotomous variables with normal PCA, preserving ordinal information). There other advantages: (i) it gives coefficients for both positive and negative dummy values, which allows a more accurate index; (ii) Moser and Felton's results suggest that a polychoric PCA index may be suitable for data pooled across time (although this needs to be demonstrated in multiple countries).

Concurrent with the writing of this chapter, Kolenikov and Angeles (2009) extended the work on polychoric PCA, examining the issues with using the Filmer and Pritchett approach of dichotomizing ordinal variables. They also investigate alternative methods of using ordinal variables in PCA, letting the ordinal variable enter PCA as if it were continuous, as well as a polychoric version. Their simulations show that PCA with ordinal variables entering directly[82] outperforms PCA with ordinal variables entering as dummies (Filmer and Pritchett approach), and does similarly to the polychoric PCA. The advantage of the polychoric PCA first component is that it explains more of the

[82] Ordinal variables can be recoded to 1, 2, 3, 4… when not already done so to minimize distance between categories. Alternatively, they also examine using ordinal variables where the values are replaced by the group means of the underlying normal variable y^* conditional on a particular category of the observed ordinal indicator $y=j$ as outlined in their paper. However, this does not significantly improve on simple ordinal values.

underlying variation. Given the computational intensity of calculating polychoric PCA, they conclude that PCA with ordinal variables entering directly is the optimal approach, with polychoric PCA to be used only if the unusual situation in which proportion of variance explained is important, and the Filmer and Pritchett approach only if there are true categorical variables (which cannot be made ordinal). Polychoric PCA is not implemented in this chapter, and the ordinal nature of variables retained in a different way (cascading).

Principal Factor Analysis

An alternative to PCA is principal factor analysis (PFA).[83] PCA is often treated as a special case of PFA, but as Jolliffe (2004) notes, the two techniques are actually distinct. The brief account here follows Jolliffe; see Gorsuch (1983) for a full account.

A main contrast between PCA and PFA is that the latter is based on an explicit model, whereas the former is not. In the case of PFA, the underlying variables **x** can be expressed as linear functions of common factors **f**, and variable specific factors or error **e**; that is, $\mathbf{x} = \mathbf{\Lambda f} + \mathbf{e}$. As Jolliffe notes, "one contrast between PCA and factor analysis is immediately apparent. Factor analysis attempts to achieve a reduction from p to m dimensions by invoking a *model* relating $x_1, x_2, \ldots, x_p$ to m hypothetical or latent variables … PCA differs from factor analysis in having *no explicit model*." (2004:151)

[83] PFA is sometimes used to refer to a variety of multivariate techniques (see Jolliffe, 2004); a standard but more narrow treatment is adopted here.

There is a multiplicity of **Λ**s which solve this; further restrictions are imposed to get a unique initial solution. The first principal factor, like the first principal component in PCA, is retained as the asset index. The initial solution can be arrived at using a number of methods, one of which is PCA.

There are other key differences between PCA and PFA. Both techniques try to reduce a large number of variables to a smaller number by exploitation of the correlation or covariance matrix; PCA focuses on the diagonal elements of this matrix, PFA on the off-diagonal. One consequence is that in PCA any individual variable that is mostly uncorrelated with the others will have its own corresponding principal component,[84] whereas in PFA common factors must have at least two variables loading. Thus PFA may require a fewer number of factors than the number of PCs required under PCA, and could result in quite different interpretations of the first principal component or factor.

An important distinction for our purposes is that changing the number of underlying variables can have drastic effects under PFA, where none of the m_2 new factors need resemble the original m_1 factors; with PCA, an additional $m_2 - m_1$ PCs are included but the original m_1 PCs are usually unaffected. This makes PFA considerably more sensitive to the choice of underlying variables.

In summary, as Jolliffe (p.165) observes, “it does not really make sense to ask whether PCA is ‘better than’ factor analysis or vice versa, because they are not direct

[84] Only that variable will have high loadings on one of the principal components.

competitors. If a model seems a reasonable assumption for a data set, then factor analysis, rather than PCA, is appropriate. If no such model can be assumed, then factor analysis should not really be used." The asset indicator-based index literature has appropriately tended to use PCA.

Sahn and Stifel (2003a) use a one-factor PFA model, with the common factor being 'household welfare', to evaluate child health and nutrition across a number of developing countries, and to explore urban–rural differences in well-being in several African countries (2003b). They prefer PFA because, unlike PCA, it does not require all of the common factors to explain the entire covariance matrix. However, it is unclear that a single-factor model is appropriate to describe the underlying structure of the various indicators usually considered in index construction. Indeed, given the different role that concepts such as income and wealth might play in determining measures of economic well-being, a multi-factor model might be preferred; at the least, it seems dangerous to assume a single-factor model, suggesting we might prefer PCA to PFA for index purposes, at least on a theoretical level. However, in many applications PCA and PFA indices are commonly found in practice to achieve similar results. The empirical section shows that this is indeed the case with respect to most asset indices.

Multiple Correspondence Analysis

Multiple correspondence analysis (MCA)[85] is similar to PCA, and is also exploratory in nature, rather than assuming an explicit underlying model as with PFA.[86] However, while PCA and PFA assume continuous, multivariate normal distribution variables, MCA does not, leading Booysen *et al.* (2005) and Burger *et al.* (2006) to prefer it to PCA. With MCA, a standard correspondence analysis is applied to an indicator matrix (such as rows of households and columns of asset or other indicators, as here). It can also be adjusted to deal with categorical levels greater than 0 or 1. An overview is given in Abdi and Valentin (2007) and a comprehensive treatment in Greenacre and Blasius (2006).

However, as Jolliffe observes, there is no need for PCA to be done on continuous variables with normal distributions unless invoking inferential techniques that depend on assumptions such as multivariate normality (see Jolliffe, 2004, subsections 3.7 and 13.1). In the current context, this might be done to test the stability of an index's weights over subsets of the sample (e.g. income or wealth quintiles), meaning for this particular purpose we would prefer the estimation errors from MCA to the biased standard errors from a PCA or PFA approach. Nonetheless, most applications of dichotomous or categorical indicator-derived indices in the literature do not rely upon statistical inference. Moreover, while PCA estimates might be biased if ordinal values

[85] MCA is a generalization of simple correspondence analysis and is known by a number of names, including optimal scaling, optimal or appropriate scoring, dual scaling, homogeneity analysis, scalogram analysis, and quantification method.

[86] Jolliffe (2004) shows that MCA is a version of PCA for discrete variables.

enter in a dichotomized manner, they do well when entering directly, as discussed. The advantage of MCA over PCA or PFA will thus depend on the purpose of an index.

Dichotomous Hierarchical Ordered Probit Model

A major difficulty with asset indices derived from PCA, PFA or MCA is in comparing across periods and places. If the analysis is run on a pooled dataset, then the weights derived are based on the variation across all of the surveys, and so while the index scale is arbitrary, it is shared by all households. However, if there are non-economic reasons driving the presence or absence of particular variables across countries or regions, then the pooled approach can be inappropriate. For example, households from significantly different climates will likely have very different ownership of air-conditioners. Similar problems can occur across periods. Having a landline in an earlier period may be a good indicator of household economic well-being, but its absence in a later period may not be, with mobile telephony having leapfrogged landlines in many developing countries. Yet an index constructed over the pooled data may treat later households as poorer. In addition, as Ferguson *et al.* (2003:2) highlight, "PCA/PFA do not provide information at which different assets or goods and services will be purchased. Finally, these two approaches do not provide prospective guidance on the best assets or goods and services to include in the future surveys to obtain more refined estimates of household permanent income."

They introduce a new approach to index construction based on a dichotomous hierarchical ordered probit model (DiHOPIT).[87] In their version of the DiHOPIT model each household begins with an (unobserved) latent variable, permanent income, and a number of observed variables (the assets and household characteristics). Each observable is assumed to be more likely to occur as a household increases its permanent income; most households will have the cheapest assets (e.g., a bicycle), fewer houses will have the more expensive (e.g., a motorbike) and only those with the highest permanent income will have the most expensive (e.g., a car). The model is then used to estimate cut-off points for each indicator variable, the level of permanent income at which a household is more likely than not to have an asset or characteristic. Households' individual responses on each variable can then be used to estimate the household permanent income.[88]

The methodology has been extended by the World Health Organization to make the DiHOPIT index comparable across countries.[89] Global cut points, calculated as the weighted means of the country-specific cut points, are used to adjust the indices for each country. Variables with high variance amongst the countries are excluded. The country indices are adjusted to the common global scale using a linear transformation,

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[87] This has been further developed and standardized by the World Health Organization (WHO) and the Harvard University Initiative for Global Health (HIGH) for use with the World Health Survey datasets. Code and documentation are available from HIGH.

[88] For development of the DiHOPIT model, see also Tandon *et al.* (2002).

[89] This description is taken from a WHO note accompanying the sample code provided by Emmanuela Gakidou and Diana Lee.

where each country's cut points are regressed against the global cut points and the coefficients applied to the country's index scores, resulting in a global index which preserves within-country rank order.

The ability to compare indices across countries or time is highly appealing. However, as with PFA, DiHOPIT is making a strong assumption in explicitly positing a specific underlying model relating the variables, with a single dimension. A multiple dimensional model would be possible but considerably more difficult. Moreover, restrictions on variables to include make it more difficult to implement over multiple existing datasets. Practically, constructing DiHOPIT indices is very computationally intensive and there are currently no pre-packaged statistical commands.[90]

Table 3.1 summarizes the non-empirical differences between the weighting methodologies, from which we can come to some initial conclusions. For researchers without an explicit model of the underlying variables, PCA and MCA are easy to implement and the most appropriate. If statistical inference based on the accuracy of weighting estimation is required, MCA is better than PCA, and if indices need to be comparable across temporally or spatially distinct surveys, then DiHOPIT may be more suitable than pooled PCA, although difficulty of implementation must also be considered.

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[90] DiHOPIT was implemented in this chapter using Stata. The code was based on samples provided by Emmanuela Gakidou and Diana Lee.

Table 3.1. Theoretical Differences in Weighting Methodologies

Method	Distributional assumption on variables	Comparison across Periods and place	Nature	Ease of implementation
PCA	Continuous, normal	No*	Exploratory	Easy
PFA	Continuous, normal	No*	Explicit model	Easy
MCA	Dichotomous or categorical	No*	Exploratory	Easy
DiHOPIT	Dichotomous	Yes	Explicit model	Difficult

Notes: * PCA, PFA and MCA can be used on data pooled across periods and places, but this is unsatisfactory for reasons discussed in the text. Polychoric PCA may be of use.

We turn now from the current methods of index construction and discuss a key limitation they all share, being uni-dimensional, and suggest two possible multidimensional approaches.

3.3.3. The Problem with a one-dimensional approach

The different concepts that indices constructed using the current measurement approaches have been claimed to represent have already been discussed; I classify them as living standards, economic security and economic well-being. One important problem with the current approaches is that they are all one-dimensional. Researchers might be interested in not only aggregate economic well-being, but also its components separately (and as Deaton (1997) suggests, it may be better to keep them separate); a one-dimensional index does not capture this. Could economic well-being even be accurately expressed as a scalar measure, given that any weighting of living standards and economic security would be somewhat arbitrary? We might prefer a multi-dimensional measure, for example, one with different dimensions corresponding to living standards (closely related to consumption), economic security in the sense of weathering shocks (determined in large part by wealth), and economic security in the sense of shocks being less likely (determined partly by sources and types of income).

A multidimensional approach would also resolve conflicts of interpretation that arise using a scalar index. For example, Bingenheimer (2007) discusses a recent paper (Shelton *et al.*, 2005) which argues that HIV prevalence increases with wealth in Africa, contrary to the popular wisdom amongst epidemiologists and development workers that it was driven by poverty. Bingenheimer points out that traditional forms of wealth, such as land and cattle, had low or negative scoring coefficients when constructing a wealth index, which can mean some households appear wealthy when considering their traditional holdings, yet poor according to their asset index score. Land, livestock holdings and close family ties may underpin the economic security of a rural household, who may nonetheless lack the assets in the index. In contrast, an a single urban worker with many of the index assets, such as electricity and a telephone, may be vulnerable to a job loss because of a lack of traditional holdings and an isolation from a kinship network. A high index score may the underlying economic insecurity. This highlights the importance of distinguishing multiple dimensions, such as living standards and economic security.

3.3.4 Potential multidimensional extensions

Separate Indices

If we could identify certain indicator variables as *a priori* representing specifically consumption, wealth or income, then any of the current weighting methods could be used to develop separate indices. This may be difficult to do in practice as many indicators represent more than one of the concepts. For example, what is garbage collection an *a priori* indicator of? If it is a service that can be purchased by each household, then it may be an income indicator, but garbage collection may also be neighborhood-dependent, in which case the location of the house will determine it. Wealthier houses may be in neighborhoods with garbage collection, but high-income low-wealth families could also rent in these neighborhoods. And many consumption indicators are determined by both income and wealth. More obviously, we might consider home-ownership to be a good wealth indicator. However, home-ownership is often high across most wealth (and income) deciles in developing countries, as it is in my data; quality of housing may be a better indicator of wealth than home-ownership itself.

The ability to separate out such concepts should be an important consideration in the design of future household surveys. Nonetheless I identify a range of variables *ex ante* as wealth indicators (predominantly asset indicators), from which to construct a separate wealth index, which is evaluated in the next section. It will probably be difficult in practice to identify income-specific indicators. Outside of head of household education and literacy, most variables are either asset ownership indicators (which *a priori* suggest wealth) or living standards (consumption) indicators.

Multi-dimensional Indices

PCA, PFA and MCA produce more than one principal component.[91] Presumably a desire for a scalar measure of economic well-being has led researchers to retain just the first component (explaining the greatest variance in the data). The multi-dimensional nature of economic well-being might be captured by retaining two or three components, each of which having a different interpretation. These components can be *rotated*, which examines combinations of components to see whether one is more ‘simple’, the meaning of which depends upon the type of rotation. It often allows a smaller number variables to load more highly on each retained component, aiding interpretation.[92]

This might produce not only distinct measures for living standards and economic security, but also a separate scalar measure for their aggregate consequence, economic well-being. For example, when PCA is used with anatomical measurements, which have positive correlations between most variables, the first unrotated principal component

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[91] For simplicity I refer to principal components (PCA), factors (PFA) and dimensions (MCA) all as components.

[92] Rotations can be orthogonal or oblique. Orthogonal rotations require the rotated components to remain uncorrelated and are the standard approach in many PCA and PFA studies. However, this is a strong assumption to make about data; in the present case, we would expect consumption, income and wealth to be correlated, as in my data. Oblique rotations allow such relationships between the rotated components.

often just indicates overall 'size', while subsequent principal components contrast some of the measurements with others, defining certain aspects of shape (see Gorsuch, 1983). It is plausible that one component might represent economic well-being and others various components.

3.4. Empirical Evaluation: What do Asset Indices Measure and Does Construction Matter?

3.4.1. Indonesian Family Life Survey

This subsection discusses the Indonesian Family Life Survey (IFLS), which I use to evaluate how asset indices relate to economic measures and whether choice of variables to include and weights to use are empirically significant. The IFLS is a longitudinal socioeconomic and health survey conducted in 13 of Indonesia's then 27 provinces, representing 83 percent of the population (Frankenberg and Karoly, 1995; Frankenberg and Thomas, 2000; Strauss *et al.* 2004). To date there have been three waves; 1993, 1997 and 2000, with a 1998 supplemental survey of a quarter of the households in the immediate aftermath of the Asian financial crisis. At the time of writing, a fourth wave is in the field and should be publically available in 2009.

The IFLS is a very rich dataset, with detailed individual and household information, including modules on consumption, income and assets, education, migration, labor market outcomes, marriage and fertility, health and health care, and household decision-making and intra-family transfers. It also includes community data on infrastructure, employment opportunities, food prices, and access to health and educational facilities. 10,435 households are in the 2000 survey used in this chapter (48 percent urban, 52 percent rural), with 14,129 female adults, 12,997 male adults and 11,307 children interviewed. Importantly, the dataset contains not only the asset and other indicators required to implement the various index methodologies, but also self-reported values of individual and household income, consumption and assets. This allows me to assess how well these relate to the asset indices constructed.

Monetary Measures of Household Economic Well-being

Income has been calculated to include wages and salaries, along with non-monetary components of remuneration, and earnings from investments, whether interest, rent, dividends, capital gains, or direct earnings from self-owned enterprises. Income also is taken to include self-production (in-kind). Consumption similarly includes expenditure and non-expenditure items; expenditure items include the purchase of all everyday items, whereas non-expenditure consumption covers self-produced goods (typically food and other agricultural products) and non-monetary remuneration items that are consumed by the household. Wealth is taken as aggregate value of all household assets and holdings, which includes not only household dwelling and valuables, such as appliances, vehicles, jewelry and furnishings, but also financial assets such as savings and investments, and business or farm assets. The data appendix contains detail on how each monetary variable was constructed from the IFLS data and how various issues were treated.

The sample distributions of household income, wealth and consumption are standard for developing countries. The wealth distribution shows a bunching near zero descending into a very long tail, resembling wealth distributions from other datasets, in both developing and developed countries. Thus, while underreporting by the rich may still be a concern, the distribution of self-reported wealth looks reasonable.[93] In the sample, 60 percent have self-reported wealth less than Rp.25m, or about USD2,800. The income distribution also looks relatively standard; a long tail with a relatively low mode towards the bottom of the left-hand side of the distribution.[94] The 90th percentile level of consumption is around Rp.22m, whereas for income is around Rp.28m, indicating that those with high incomes do not consume all of it. Otherwise, the consumption distribution is similar to that of income.

Simple correlations between logs of income, wealth and consumption are given in Table 3.2. Not surprisingly, since income and wealth are determinants of consumption, and

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[93] Note, taking the log of wealth, used throughout the chapter, excludes those households with zero wealth. However, this represents only 120 households, or one percent of the initial sample. Most households have non-zero wealth, even if it is meager, such as poultry or basic furniture and utensils.

[94] Of concern in the income distribution are 575 households reporting zero income (but not a missing value). While zero wealth is relatively plausible, zero total household income seems less likely. Since these households represent only about six percent of the sample, they are excluded from most of the analysis; given that this chapter explores methodological concerns rather than causal relationships and nationally representative results, this exclusion seems tolerable. Unlike income, there are very few households with near-zero consumption, indicating those with very low incomes are somehow consuming above this, possibly due to misreporting of in-kind production or transfers, although these have been included in income calculations.

since wealth is in part determined by saved income in previous periods, we see reasonable correlation between all three. Various consumption measures are also regressed on income and wealth and a set of controls.[95] A dollar of income is more important than a dollar of wealth in determining consumption; given the near-zero wealth of much of the sample, this is unsurprising. However, this is driven by food consumption; wealth is more important when we consider only non-food consumption. In addition, rural households are more likely to consume in-kind (self-produced), with income not significant. Despite these differences, both income and wealth remain significantly correlated with consumption. However, moderate correlations between income, wealth and consumption, while related, should not be used as direct substitutes for each other.

Table 3.2. Simple correlations of income, wealth and consumption

	Correlations				Rank Correlations			
	Log W	Log M	Log I	Log C	Log W	Log M	Log I	Log C
Log Wealth	1.00	0.48	0.43	0.45	1.00	0.47	0.47	0.46
Log Marketable Wealth		1.00	0.38	0.51		1.00	0.43	0.49
Log Income			1.00	0.48			1.00	0.51
Log Consumption				1.00				1.00

Notes: Log W is Log Wealth, Log M is Log Marketable Wealth, Log I is Log Income, Log C is Log Consumption. Marketable wealth is defined as cash, securities, receivables and jewelry.

Asset Indicators and Household Characteristics

The IFLS household variables cover a wide range of categories, including asset ownership, housing quality, water quality, health quality and social services, as well as

[95] Not shown; available upon request from the author.

head of household characteristics (the full range is listed in Table 3.4). Despite this, there are some limitations to using this variable set to construct an asset index. In particular, some asset categories allow for too much variation in value. For example, the vehicle indicator includes bicycles, motorbikes, cars and boats. Ownership of any one of these differently-valued assets results in a positive indicator; for our purposes they would be better broken out separately. Similarly, livestock does not distinguish between a few chickens and a number of cows, and the appliances indicator covers washing machines as well as radios and tape recorders. The IFLS goes on to ask for the value of assets within each of these categories, so the distinctions are less critical for non-index uses. However, most surveys do not ask asset value, hence the need for asset indices. For these purposes a finer breakdown is desirable.

As well as their *a priori* suitability for an asset index, we can also examine how the presence of asset and household characteristics indicators varies across income, wealth and consumption deciles. If an index constructed from these indicators is to be a reasonable measure of economic well-being, then households in higher monetary deciles should have higher average indicators; for example, they would be more likely to own particular assets, or to have higher quality housing. Table 3.3 contains selected indicator summary statistics by household wealth decile.[96]

[96] A full summary of variables by decile is available upon request, as are statistics by consumption and income deciles, which are similar. Note that heads of households in the bottom two deciles have more years of education on average then households in the third to sixth deciles. This could raise concerns that some wealthier houses are underreporting their assets, since higher education is usually an indicator of

Of interest is home-ownership, which is at 73 percent by the third decile, and relatively stable around 90 percent for the wealthiest half of homes. This high level of home-ownership across wealth and income levels in the data mirrors findings from other developing countries (e.g. Fay *et al.*, 2002; Torche and Spilerman, 2007, 2008); it is quality of housing that is more variable. Thus while home-ownership is a store of wealth, it may not be a good indicator of wealth.[97]

Most asset indicators increase monotonically with wealth. As expected, the presence of asset and positive household characteristics indicator variables tend to increase in wealthier households, while negative indicators decline, suggesting that these household variables form an appropriate basis for an asset index. What such an index measures is explored next.

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higher income and wealth. However, the heads of households of the bottom two deciles are on average considerably younger (36.5 and 41.5 years old) than the rest of the heads (45 years or older), which indicates a household life cycle effect, where well-educated but young households have not had time to accumulate much wealth. Furthermore, average education increases monotonically with income deciles as expected, which is less influenced by the savings life cycle.

[97] I code the 25 percent who do not own as 0 on the ownership dummy. However, of this remaining 25 percent, 60 percent occupy and 40 percent rent. In the future it may be worth including another dummy here to capture this additional variation

Table 3.3. Asset and other indicators by household wealth decile

Panel A: Assets Indicators

Decile	House	Building	NF Land	Livestk.	Vehicle	Appl.	C&S	Receiv.	Jewel.	Furn.	Other	# Ass.	HH Ass.
1	0.20	0.02	0.02	0.01	0.15	0.42	0.17	0.07	0.36	0.76	0.24	2.40	0
2	0.50	0.03	0.07	0.03	0.28	0.64	0.18	0.08	0.49	0.95	0.36	3.59	2
3	0.73	0.05	0.12	0.04	0.32	0.67	0.19	0.06	0.50	0.98	0.38	4.00	5
4	0.79	0.05	0.15	0.05	0.40	0.73	0.21	0.09	0.57	0.98	0.40	4.40	10
5	0.82	0.07	0.14	0.05	0.44	0.79	0.24	0.10	0.62	0.99	0.41	4.65	15
6	0.87	0.09	0.19	0.04	0.45	0.84	0.24	0.11	0.65	0.99	0.43	4.89	23
7	0.90	0.11	0.21	0.03	0.50	0.87	0.35	0.13	0.68	0.99	0.42	5.18	36
8	0.89	0.17	0.23	0.03	0.57	0.91	0.39	0.17	0.72	0.99	0.40	5.47	61
9	0.91	0.23	0.27	0.03	0.60	0.93	0.43	0.17	0.73	0.99	0.40	5.68	119
10	0.89	0.29	0.30	0.02	0.63	0.90	0.52	0.22	0.75	0.98	0.40	5.89	1,500
Sample	0.75	0.11	0.17	0.03	0.43	0.77	0.29	0.12	0.61	0.96	0.38	4.61	175

Notes: House is dwelling occupied; Building is any other building; NF Land is non-farm land; Livestk is livestock, poultry and fishpond; Vehicle is cars, boats, bicycles, motorbikes; Appl. is household appliances, such as radiom tape recorder, TV, fridge, sewing or washing machine; C&S is cash and securities, which include savings, certificates of deposit and stocks; Receiv. is non-business receivables; Jewel. is jewelry; Furn. is household furniture and utensils; # Ass. is number of asset categories owned (from Panel A); HH Ass. is aggregate value of assets in millions of Rp

Table 3.3. Asset and other indicators by household wealth decile (cont.)

Panel B: Selected Other Indicators

	Housing Quality							Water Quality		App.	Health	Head of Household	
Decile	Vent.	M.Yard	Kit.Bed	No toilet	LQ roof	Elec.	Rooms	Pump	Open	Number	Stagnant	Age	Education
1	0.65	0.51	0.11	0.48	0.08	0.86	3.89	0.59	0.09	0.31	0.15	36.45	6.44
2	0.67	0.49	0.10	0.51	0.07	0.85	4.13	0.48	0.13	0.47	0.13	41.59	5.70
3	0.68	0.55	0.06	0.51	0.05	0.81	4.43	0.43	0.15	0.48	0.12	45.09	5.26
4	0.75	0.62	0.05	0.46	0.04	0.87	4.65	0.44	0.14	0.58	0.11	45.07	5.41
5	0.77	0.62	0.06	0.40	0.04	0.88	5.03	0.48	0.14	0.72	0.09	44.77	5.66
6	0.82	0.64	0.03	0.32	0.02	0.93	5.37	0.54	0.12	0.78	0.10	46.87	5.67
7	0.85	0.66	0.04	0.29	0.01	0.94	5.73	0.53	0.10	0.96	0.09	46.95	6.50
8	0.87	0.68	0.04	0.19	0.01	0.96	6.20	0.65	0.07	1.20	0.08	47.78	7.56
9	0.87	0.68	0.03	0.16	0.01	0.97	6.71	0.72	0.06	1.48	0.05	48.78	8.07
10	0.85	0.70	0.03	0.18	0.01	0.96	7.15	0.70	0.07	1.53	0.07	47.20	8.43
Sample	0.78	0.62	0.06	0.35	0.03	0.90	5.34	0.56	0.11	0.85	0.10	45.03	6.45

Notes: Vent. is house well-ventilated; M.Yard is a moderate-sized yard; Kit.Bed is kitchen and bedroom are in the same room; LQ roof is low quality materials (foliage, palm leaves, grass, bamboo); Elec. is house uses electricity; Rooms is number of rooms; Pump is drinking water either piped or from a pump; Open is drinking water from an open source; App. Number is number of appliances owned (from fridge, TV, radio, which were the only ones asked separately); Stagnant is presence of stagnant water around the house.

3.4.2 Constructing the asset index

As discussed, index construction can vary by both choice of weighting methodology and set of underlying variables. I begin by examining how sensitive indices are to these choices, constructing indices using all four weighting approaches (PCA, PFA, MCA and DiHOPIT), and across a range of different variables used previously in the literature, constructing indices which approximate each of these formulations where possible. The formulations are described below and summarized in Table 3.4.

The *FP* index is created to follow as closely as possible the set of underlying variables used in Filmer and Pritchett's well-known formulation (2001), similar in construction to McKenzie's index (2005), and includes housing and water quality variables, appliances and assets.[98] All the other formulations in the literature also use variables from each of these categories. *SS* approximates Sahn and Stifel's index (2003a), also comparable to Booysen *et al.* (2005) and Burger *et al.*'s (2006) indices; in addition to housing and water quality variables, appliances and assets, it includes head of household education. *FTGM 1* and *FTGM 2* are formulations from Ferguson *et al.* (2003). As well as variables from the standard categories, FTGM 1 includes a greater number of head of household covariates (age, education and employment), and the number of people in the household. FTGM 2 has the standard categories plus variables from health quality

[98] FP differs from Filmer and Pritchett in missing clock/watch, radio, and sewing machine (not present in the IFLS; an appliances indicator is included instead), and motorcycle and car indicators (a vehicle indicator is used). *FP 2* was also constructed, which excludes the inexact appliances and non-farm land indicators (Filmer and Pritchett use 'Owns > 6 Acres Land'). However, the results for FP 2 differ only marginally from FP and are not discussed.

(garbage collected), head of household (literacy), and number of adults and number of children.

I also examine two further formulations. Following the previous discussion on the choice of variables I construct an *Asset Only* index which comprises only the asset ownership indicators and number of rooms. This uses very few of the variables used in the other formulations, so is potentially complementary rather than a substitute: this is the idea behind the separate index multi-dimensional extension. Finally, an *All* index is created, using all of the underlying variables available. This means 58 variables from housing, water and health quality, appliances and assets, social services, head of household characteristics, and number of adults and children in the household. For each formulation I construct four indices, using PCA, PFA, MCA and DiHOPIT to obtain weights. Next I evaluate how similar these different indices are to each other, and how well the correlate with monetary measures.

3.4.3 Evaluating the asset index

Correlations Amongst Indices

The absolute weights under each method are arbitrary in that they do not correspond to any real-world measure, and so are not strictly comparable across methods. In Table 3.5, using the FP formulation as an example, I normalize the weights as a proportion of

Table 3.4. Variables by index formulation

Index	Indicator Category	Indicators
Filmer and Pritchett (FP)	Housing Quality	Separate kitchen and bedroom, high and low quality floor, wall and roofing materials, cooks with biomass, toilet with septic tank, no toilet.
	Water Quality	Pumped drinking water, drinking water not from open source
	Assets	Nonfarm land, vehicle, fridge, TV, appliances
	Other Indicators	Electricity, number of rooms
Sahn and Stifel (SS)	Housing Quality	Low quality floor materials, toilet with septic tank, no toilet.
	Water Quality	Pumped drinking water, drinking water not from open source
	Assets	Vehicle, fridge, TV, appliances
	Head of Household	Education
Ferguson, Tandon, Gakidou and Murray (FTGM 1)	Housing Quality	Separate kitchen and bedroom, toilet with septic tank
	Water Quality	Pumped drinking water
	Assets	Other house/building, vehicle, TV, appliances, furniture
	Head of Household	Age, education, employed
	Other Indicators	Number in Household, 2+, 3+, 4+, 5+, 6+ rooms
Ferguson, Tandon, Gakidou and Murray (FTGM 2)	Housing Quality	High quality floor and walls, toilet with septic tank, toilet without septic tank
	Water Quality	Pumped drinking water
	Assets	Fridge, TV, modern stove, appliances
	Health Quality	Garbage collected
	Head of Household	Literacy
	Other Indicators	Electricity, number of adults, number of children, 2+, 3+, 4+, 5+, 6+ rooms
Asset Only	Assets	House occupied, other house/building, nonfarm land, furniture, jewelry, receivables, vehicle, Savings/certificates/deposits/stocks, fridge, TV, modern stove, appliances
	Other Indicators	Number of rooms
All Variables	Housing Quality	Well-ventilated house, moderate-sized yard, separate kitchen and bedroom, high and low quality floor, wall and roofing materials, cooks with biomass, toilet with septic tank, toilet without septic tank, no toilet, house on or near stables, outside kitchen.
	Water Quality	Drinking water located in house, boil drinking water, buy washing water, Pumped drinking water, drinking water not from open source, pumped washing water, washing water not from open source, drinking water same as washing.

Table 3.4. Variables by index formulation (cont.)

Assets	House occupied, other house/building, nonfarm land, furniture, jewelry, receivables, vehicle, savings/certificates/deposits/stocks, fridge, TV, modern stove, appliances
Health Quality	No animal or human waste, no trash, no stagnant water around house, sewage runs into drainage ditch, garbage collected, well-kept yard.
Social Services	Health Card, letter of poor, participates in health fund, receives aid.
Head of Household	Age, single, married, education, literacy, economically active, employed.
Other Indicators	Electricity, number of rooms, number in household, number of adults, number of children.

the highest weight for each method allowing comparison of magnitudes. Their relative ranking within each method are also shown.[99] As the table illustrates, PCA, PFA and MCA assign similar rankings and proportional weights to each variable. For example, high quality floor materials is weighted as 92 percent of the maximum weight under PCA, 92 percent under PFA (71 percent on scoring coefficient) and 100 percent under MCA. The signs are always consistent, except for quality of roofing materials in the FP formulation, when PFA and MCA have perverse signs. The DiHOPIT cut points are less comparable, given the different nature of the methodology. Positive cut points are less common and negative cut points generally of greater magnitude, evident in absolute scores, not shown here. As arbitrary scores, this means little; rather it is the cut point relative to other cut points that is informative. In this respect DiHOPIT appears to differ from the other three methodologies in giving greater weight to adverse indicators. Furthermore, there are a number of differences in relative rankings.

[99] Results for the other formulations are available upon request.

Thus, PCA, PFA and MCA produce very similar weights, while DiHOPIT differs to an extent. PCA, PFA and MCA indices also have very high correlations between themselves for any given variable formulation (0.98 or higher, as seen in the shaded main diagonal in Table 3.6). Despite differences in weighting, DiHOPIT-based indices also correlate highly with other weightings of the same formulation (0.83 or higher and generally above 0.90).[100] Furthermore, the choice of variable formulation generally does not change the results, with some exceptions. As the shaded cells off the main-diagonal show, indices based on different variable sets but with the same weights correlate strongly with each other (generally 0.80 or higher), except for the first FTGM formulation (0.60-0.92) and the Asset Only Index (0.63-0.83); these exceptions may be because, as we see later, these two formulations correlate more strongly with wealth then the others. As predicted in the method section, PCA indices are less sensitive to different formulations than PFA (PFA indices for two different formulations have lower correlations than PCA indices for the same two formulations). Even indices based on both different formulations and weights have very high correlations, generally 0.80 and higher (FTGM 1 and the Asset Index again being slight exceptions). Thus, initially, the asset indices appear fairly robust to different weighting approaches and different underlying variable formulations.

[100] Throughout the chapter, rank correlations are almost always stronger than the standard correlations reported here, but as they have the same pattern they are not presented.

Table 3.5. Weights for FP index – relative rankings

		Proportional Weights				Relative Rankings				
		PCA	PFA		MCA	PCA	PFA	MCA	DiHOPIT	
Indicator Category	Indicator	FL/SC	FL	SC	Coord.	FL/SC	FL	Coord.	Cut	Rank
Housing Quality Characteristics	Separate kitchen and bedroom	0.24	0.18	0.04	0.38	12	12	11	-0.26	21
	High quality floor materials	0.92	0.92	0.71	1.00	3	2	1	-0.15	15
	Low quality floor materials	-0.88	-0.88	-0.19	-0.98	20	20	19		
	Not low quality floor materials								-0.19	16
	High quality wall materials	0.91	0.78	0.26	0.72	4	4	6	-0.05	10
	Low quality wall materials	-0.73	-0.62	-0.12	-0.90	17	17	18		
	Not low quality wall materials								-0.21	20
	High quality roof materials	0.17	-0.33	-0.09	-0.88	13	16	17	-0.06	11
	Low quality roof materials	-0.43	0.12	0.09	0.14	16	13	12		
	Not low quality roof materials								-0.30	23
	Cooks with biomass	-0.84	-0.70	-0.17	-0.65	18	18	15	-0.08	12
	Toilet with septic tank	1.00	1.00	0.00	0.74	1	1	3	0.02	5
	Toilet without septic tank	-0.26	-0.27	-0.56	-0.26	15	15	14	-0.04	9
	No toilet	-0.84	-0.84	-1.00	-0.66	19	19	16		
Water Quality Characteristics	Pumped drinking water	0.76	0.63	0.19	0.57	5	5	9	-0.01	6
	Drinking water not open source	0.53	0.43	0.09	0.64	10	10	8	-0.20	17
Appliances	Fridge	0.70	0.56	0.13	0.74	8	8	4	0.18	1
	TV	0.96	0.82	0.30	0.72	2	3	5	-0.03	7
Assets	Nonfarm land	0.09	0.07	0.02	0.09	14	14	13	0.15	2
	Vehicle	0.51	0.40	0.12	0.39	11	11	10	0.03	4
	Appliances	0.75	0.62	0.19	0.66	7	6	7	-0.11	13

Table 3.5. Weights for FP index – relative rankings (cont.)

Other Indicators	Electricity	0.76	0.61	0.16	0.95	6	7	2	-0.21	19
	Number of rooms	0.68	0.55	0.13	0.00	9	9			
	Rooms: 1 or more								-1.00	24
	Rooms: 2 or more								-0.28	22
	Rooms: 3 or more								-0.21	18
	Rooms: 4 or more								-0.12	14
	Rooms: 5 or more								-0.04	8
	Rooms: 6 or more								0.04	3

Note: Sum of squares (column-loading) = 1. FL is factor loading, SC is scoring coefficient, Coord. is difference between coordinates for 0 and 1 on each variable. All weights are scaled to be proportional to greatest weight. Cut. Is cut point for DiHOPIT.

Table 3.6. Correlations between indices

		FP				SS				FTGM1			
		PCA	PFA	MCA	DH	PCA	PFA	MCA	DH	PCA	PFA	MCA	DH
FP	PCA	1.00											
	PFA	0.98	1.00										
	MCA	1.00	0.98	1.00									
	DiHOPIT	0.93	0.89	0.94	1.00								
SS	PCA	0.92	0.92	0.92	0.88	1.00							
	PFA	0.91	0.91	0.90	0.87	0.99	1.00						
	MCA	0.92	0.91	0.91	0.87	1.00	0.99	1.00					
	DiHOPIT	0.86	0.85	0.85	0.81	0.84	0.83	0.84	1.00				
FTGM1	PCA	0.67	0.63	0.68	0.84	0.68	0.68	0.68	0.62	1.00			
	PFA	0.65	0.60	0.66	0.83	0.64	0.64	0.64	0.58	0.99	1.00		
	MCA	.	.	.	.	.	.	.	.	.	.	.	
	DiHOPIT	0.67	0.63	0.68	0.79	0.72	0.71	0.71	0.70	0.90	0.87	.	1.00
FTGM2	PCA	0.91	0.87	0.92	0.95	0.85	0.85	0.85	0.80	0.90	0.89	.	0.85
	PFA	0.89	0.86	0.90	0.94	0.84	0.84	0.84	0.79	0.92	0.92	.	0.85
	MCA	0.89	0.85	0.88	0.94	0.84	0.84	0.80	0.75	0.89	0.88	.	0.81
	DiHOPIT	0.81	0.78	0.79	0.87	0.80	0.80	0.74	0.69	0.87	0.85	.	0.83
Asset Only	PCA	0.72	0.66	0.72	0.80	0.77	0.75	0.78	0.75	0.77	0.74	.	0.76
	PFA	0.74	0.68	0.74	0.81	0.79	0.77	0.80	0.76	0.77	0.75	.	0.77
	MCA	0.73	0.67	0.74	0.82	0.78	0.75	0.76	0.73	0.79	0.76	.	0.78
	DiHOPIT	0.66	0.60	0.66	0.80	0.67	0.66	0.67	0.63	0.90	0.89	.	0.82
All	PCA	0.95	0.91	0.94	0.91	0.90	0.88	0.90	0.89	0.73	0.70	.	0.74
	PFA	0.95	0.93	0.95	0.91	0.91	0.89	0.91	0.89	0.72	0.69	.	0.74
	MCA	0.94	0.91	0.91	0.89	0.90	0.88	0.83	0.81	0.67	0.64	.	0.68

Table 3.6. Correlations between indices (cont.)

		FTGM2				Asset Only				All		
		PCA	PFA	MCA	DH	PCA	PFA	MCA	DH	PCA	PFA	MCA
FTGM2	PCA	1.00										
	PFA	1.00	1.00									
	MCA	1.00	1.00	1.00								
	DiHOPIT	0.94	0.93	0.93	1.00							
Asset Only	PCA	0.81	0.81	0.82	0.76	1.00						
	PFA	0.83	0.83	0.84	0.78	1.00	1.00					
	MCA	0.83	0.83	0.83	0.77	0.99	0.99	1.00				
	DiHOPIT	0.84	0.85	0.78	0.72	0.93	0.91	0.92	1.00			
All	PCA	0.90	0.88	0.90	0.84	0.79	0.81	0.80	0.72	1.00		
	PFA	0.90	0.88	0.90	0.83	0.77	0.79	0.78	0.70	1.00	1.00	
	MCA	0.91	0.89	0.91	0.85	0.78	0.79	0.77	0.63	1.00	0.99	1.00

Correlations with Monetary Measures

How well the indices correlate with monetary measures is now examined, as well as whether the weighting methodologies or variable formulations affects these correlations. The results appear in Table 3.7. The indices correlate consistently well with log consumption (ranging from 0.47-0.62), less consistently well with log wealth (0.35-0.62) and only moderately with log income (0.34-0.43).[101]

The weighting approach does not lead to consistent differences; generally the results are similar for a given formulation, and when they vary, such as with DiHOPIT, it is not consistently higher or lower. However, the choice of variables is more important. All formulations correlate well with consumption (0.47 lowest, 0.55 average), but there is considerably more variation with wealth. The Asset Only Index (using only asset ownership indicators and number of rooms) not only has the strongest correlations with log wealth (0.55-0.62) but also with log consumption (0.56-0.62). The FTGM formulations also correlate well with log wealth (0.47-0.53). No formulation correlates particularly well with log income (0.43 highest, 0.39 average).

This indicates that while the underlying variables used to construct the indices often produce similar results, it is possible for different formulations to correlate with

[101] I use logs of the monetary measures, preferring ratio measures to interval measures: one dollar is worth more to a poor household than a rich household. Rank correlations, not shown, have the same pattern as the normal correlations shown, but are slightly stronger. The DiHOPIT results are very similar to those found by Ferguson *et al*. (2003) for their Greece and Peru datasets.

different monetary measures, suggesting that developing separate wealth and consumption measures could be fruitful.[102]

Table 3.7. Correlation between monetary variables and indices

		Entire Sample			Excl. Top Income Decile		
		Log W	Log I	Log C	Log W	Log I	Log C
FP	PCA	0.38	0.37	0.53	0.39	0.37	0.53
	PFA	0.35	0.34	0.49	0.37	0.34	0.49
	MCA	0.39	0.37	0.53	0.40	0.37	0.53
	DiHOPIT	0.48	0.37	0.54	0.47	0.38	0.51
SS	PCA	0.39	0.40	0.55	0.40	0.40	0.55
	PFA	0.38	0.39	0.53	0.39	0.39	0.53
	MCA	0.39	0.38	0.56	0.40	0.38	0.55
	DiHOPIT	0.37	0.39	0.56	0.35	0.40	0.54
FTGM1	PCA	0.52	0.37	0.49	0.50	0.37	0.49
	PFA	0.50	0.35	0.47	0.49	0.35	0.46
	MCA	.	.	.	.	.	.
	DiHOPIT	0.53	0.42	0.59	0.51	0.44	0.56
FTGM2	PCA	0.47	0.40	0.55	0.47	0.40	0.55
	PFA	0.48	0.39	0.54	0.48	0.39	0.54
	MCA	0.48	0.39	0.56	0.48	0.39	0.56
	DiHOPIT	0.48	0.43	0.58	0.46	0.46	0.55
Asset	PCA	0.56	0.42	0.61	0.54	0.41	0.56
	PFA	0.55	0.42	0.61	0.52	0.41	0.57
	MCA	0.57	0.43	0.62	0.55	0.41	0.57
	DiHOPIT	0.62	0.39	0.56	0.60	0.38	0.51
All	PCA	0.40	0.40	0.56	0.40	0.40	0.56
	PFA	0.40	0.40	0.55	0.40	0.40	0.55
	MCA	0.40	0.40	0.58	0.41	0.40	0.58

Notes: 1: Log Wealth; 2. Log Income; 3. Log Consumption.

Summarizing, most indices in the literature, regardless of weighting methodology or underlying variables used, work best as a proxy for consumption (0.47-0.62 correlation), which corresponds most closely to living standards. Three formulations are also good wealth measures, especially the Asset Only Index. That this index correlates strongly is unsurprising, being based strictly on *a priori* wealth indicators. Both FTGM formulations have a variable indicating the household's age (head of

[102] The conclusions from the simple correlations above are confirmed when we regress each index on log wealth, log income and a set of controls (urban dummy, household size, educational attainment of head-of-household and a district dummy). Table omitted but available upon request.

household age, number of adults and number of children); which may indicate how long the household has had to potentially accumulate wealth. No formulation performs particularly well as an income measure, not even indices including head of household education or literacy. Together the wealth and income results suggest that the inclusion of head of household covariates is undesirable; the methodological reasons for keeping them separate were previously discussed, and empirically they either add nothing (in the case of income) or better results can be obtained without them (in the case of wealth). This is consistent with Ferguson *et al.* (2003) who also find inclusion of household covariates adds no benefits. To the extent that income is correlated with consumption, the use of these indices as measures of income is not inappropriate; however, they are probably better considered consumption measures (or wealth when constructed appropriately) than a true measure of income.

I also explored whether separate measures of wealth, consumption and income could be obtained through a multidimensional index, and whether this offers an advantage to the separate indices discussed above. More than one principal component was retained, and various orthogonal (varimax, quartimax, equamax, parsimax, entropy) and oblique (promax, oblimax, quartamin, oblimin) rotations performed using each variable formulation. This method requires considerably more work, but initial results suggested that across all formulations the unrotated first component usually measures consumption while the unrotated second correlates most strongly with either wealth or income, albeit at more modest levels. Rotation often improves result. However, generally researchers will not have income, wealth and consumption correlations to identify particular components. It is important that we can identify different components as consumption or wealth from the factor loadings alone. Is it possible to determine the nature of each component before and after rotation? In all formulations, the unrotated first component is primarily a consumption measure (although it also correlates highly with wealth for FTGM 1 and Asset Index as seen in Table 3.7). As a general rule then, we might expect to see similar loadings on the first component before and after rotation. Second, if the second component is an indicator of income or wealth, we should see high factor loadings on *a priori* wealth indicators such as age or *a priori* income indicators such as education. This approach needs to be explored in much more depth and results are not presented here. However, there is merit in further exploration of a multiple component approach, particularly if combined with survey instruments designed for such purposes.

3.4.4 Questions of construction

We now turn to more specific questions of construction. How should we treat categorical and ordinal variables? Can we better discriminate amongst the wealthy? How many variables should we include? Can we beneficially aggregate related variables?

Categorical and Ordinal Variables

An ordinal variable such as number of rooms can be broken into a series of dummies: one, two, three, four rooms, more than four rooms, for example (with an omitted category). Continuous variables, such as floor area can be first be made ordinal (*e.g.* <100m^2, 100-200 m^2, 200-300 m^2 and 300+ m^2), as well as then dichotomized. This is a common practice in the literature, although variables can enter PCA and PFA categorically, ordinally or continuously and MCA ordinally or categorically. Recall that Kolenikov and Angeles (2009) find that ordinal and continuous variables are best entering PCA directly, and this may be the best way to treat them.

An alternative approach to ordinal variables is to convert them to a series of cascading dummy variables; the World Health Organization does this in the implementation of DiHOPIT. Rather than dichotomize ordinal variables such as number of rooms in a strict indicator sense, where a separate dummy is created for each categorical response – one room, two rooms, three rooms, and so on (each household registers 1 for a single dummy and 0 on all the rest), they cascade the dummies, so each household registers 1 for each dummy up until the number of rooms they have: this effectively changes the dummies to one or more rooms, two or more rooms, three or more rooms and so forth. Using cascading variables keeps the information inherent in the ordinal ranking of the underlying variable. I compared the use of cascading ordinal variables to dichotomized ordinal variables. Cascading generally makes small but inconsistent improvements in correlations with monetary measures.[103] This is consistent with the Kolenikov and Angeles predictions; it seems that entering ordinal variables directly is most appropriate.

Categorical variables – variables whose different categories cannot be assigned a 'better' or 'worse' value, such as religion – remain difficult to treat. Kolenikov and

[103] Results available upon request.

Angeles outline a structural modeling approach which is unlikely to find favor in the field due to its complexity of implementation, and they themselves recommend, reluctantly, entering categorical variables as dummies. Alternatively, they can be forced to take an ordinal value: for example, a categorical variable for region might be assigned an ordinal value based on the poverty rate or average GDP per capita in the region, or a religion variable the average income for that religion where national data exist on this. In the case of a true categorical variable or one that does not easily dichotomize, another alternative is to drop it completely. If different values do not plausibly affect economic well-being, then it is probably unnecessary to include it.

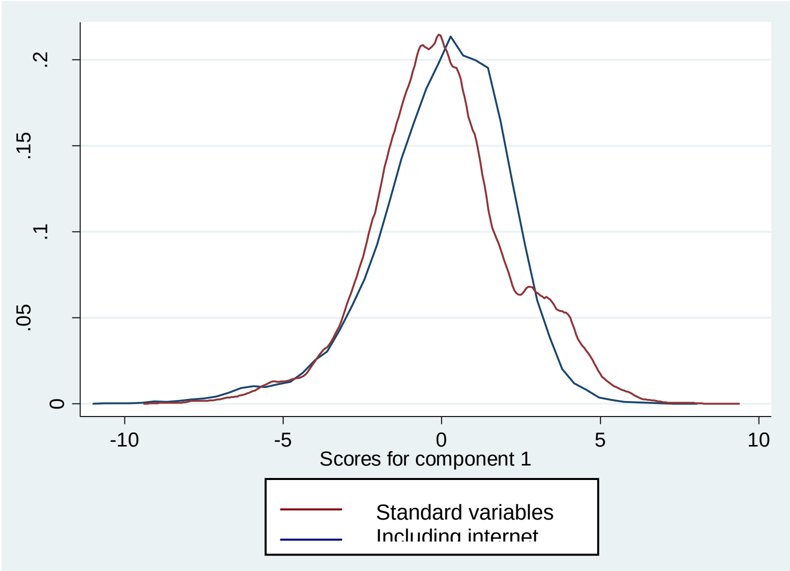
Discriminating Amongst the Wealthy

As noted, many of the indicator formulations and weighting schemes do not discriminate well amongst the wealthy. This may be a concern for some uses of an asset index, but is not surprising given the nature of the indicator variables collected in the IFLS and similar datasets. The surveys generally ask about relatively rudimentary living conditions and seldom about consumption or durable items that might separate richer households, such as ownership of a computer or access to the internet.

I present the results from analysis of the Brazilian 2004 PNAD data (a national labor force survey of about 300,000 people). Figure 3.2 shows two distributions of an index constructed using the typical underlying variables, with one exception. The first distribution (right-most) includes only the standard variables. The second distribution (left-most) includes whether the household has a computer and internet access. We can see that adding this additional variable when constructing the index changes the distribution not inconsiderably, moving some households from the middle of the distribution rightwards (wealthier) while others move leftwards (poorer); the inclusion of a single 'modern' variable gives significantly better discrimination amongst the upper half of the distribution. Other variables that might discriminate amongst the wealthy could include dedicated retirement savings accounts, overseas holdings, cars per household, and broadband rather than dial-up. There are doubtless many others; the choice of variables will always require researchers to be quite familiar with their cultural and economic setting.

In addition, there is a related question of how stable the loading factors and scoring coefficients are across subsets of the population. Scoring coefficients determined from PCA across an entire population may be quite inappropriate for discriminating amongst the poor or wealthy, whom may either all have or not have a particular characteristic or asset. In analysis using PCA not presented here, I find that the scoring coefficients for underlying variables are indeed quite different across wealth or income quintiles. Weights derived from MCA could be used to test whether these differences are statistically significant. This is left to future research.

Fig. 3.2. PNAD index distributions



Number of Variables to Include

Ferguson *et al.* (2003) split their variable set in two, alternating variables as they move down the latent permanent income ladder; that is, the first set takes the variable with the highest cut-point, the second set the second highest variable, the first set the third highest and so on. They find that the separate DiHOPIT estimators constructed from each half-set are highly correlated with each other (0.93) and nearly as well-correlated with consumption and income as the original estimator based on all variables, concluding that this "shows the potential to undertake item reduction in surveys and obtain similar estimates of household permanent income or wealth using many fewer variables". I find similar results. The Asset Only index variable set is split it in two based on the cut-point rankings from the DiHOPIT analysis. Separate PCA indices from these two datasets are then constructed. Like Ferguson *et al.*, I also find a high correlation between the two indices (0.96) with correlations between each index and consumption (0.61) and wealth (0.54 and 0.56) remaining at similar levels to the PCA index using the variables from both sets.

This suggests that an accurate index can be derived from a parsimonious but well-selected variable set. The basic factor is having some information (or at least an educated guess) about the 'discriminant power' of the set of variables chosen across the entire distribution. If the number of variables is limited, but they adequately discriminate across the entire distribution, they should suffice. If it is uncertain whether the set of variables adequately discriminates, it is difficult to determine whether they are sufficient.

Counting Variables

Often a number of variables can be grouped thematically. In the IFLS, for example, a well-ventilated house, a moderate-sized yard, a separate kitchen and bedroom, an inside toilet and high quality roof, wall and floor quality, could be considered housing quality characteristics. Consequently, instead of allowing indicators to enter the index individually, we could count the positive indicators and include this aggregate variable instead. Similarly, count measures can be developed from the IFLS for water quality, appliances, assets, health quality, and social services, as well as total number of assets categories owned (refer to Table 3.4 for a full breakdown of each category).

Using count variables may result in more accurate indices. They allow more flexibility for households to manifest choices over consumption or investment in assets. A wealthy household may choose not to own a television, despite being able to afford one; in this case their index score will be less accurate if variables enter separately as the lack of television is treated as less ability to purchase one. Similarly, some indicators may display variation not for economic reasons but cultural, geographic or climatic ones. For example, two households of the same economic means but in different locations may have a different tendency to own an air-conditioner or use a car.[104] By allowing similar variables to enter the index as part of a categorical count, non-economic differences such as these are allowed for; the assumption is that while different households may choose different assets to own, those of similar economic means will own a similar total number of assets. However, as previously discussed, it is important that the average values of asset types being added are not wildly different.

I examine the use of counts of categorically similar variables on a range of index performances, allowing variables to enter either individually or as part of a categorical count. Formulation 1 uses counts of non-asset household characteristics, such as housing, water and health quality, and social services.[105] Formulation 2 introduces a count for asset ownership. It also allows number of rooms, electricity and home ownership to enter separately. Formulations 3 and 4 examine whether these additional variables drive results by dropping count of assets, and number of rooms and electricity respectively. Table 3.8 presents the results. Formulations 2-4 suggest, irrespective of weighting methodology, that correlations with wealth are

[104] As an individual living in New York City, I am quite aware that a car can be a hindrance as well as an asset; lack of car ownership in New York is a not a good predictor of being a poor household, in comparison to much of the rest of the US.
[105] They also include a count of 'appliances', but in the IFLS this is just fridge, television and modern stove.

consistently higher when using count variables, driven mainly by the use of an asset count variable: formulation 3 drops this count and loses much of the increase; formulation 4 keeps the asset count and drops number of rooms and electricity, with similar results to formulation 2.[106] Those with income and consumption are generally the same or slightly lower.

These results suggest that an index allowing for choice in asset ownership will be a better measure of wealth; the number of assets a household owns is more important than which particular ones it owns, within a given value range. Asset counts do not affect consumption or income correlations very much, and non-asset counts have small effects. It should be noted that a simple count has been used in this initial analysis, and that simply counting indicators within a category is itself an arbitrary weighting; we might, for example, consider a PCA index within each category. However aggregated, this is a promising area for future research. In particular, the ability of count variables to ameliorate cultural and temporal differences in the manifestation of household characteristics means they could be of use in pooled PCA for cross-survey comparable indices.

[106] It was noted earlier that the asset categories in the IFLS are not ideal for index purposes, being too broad in value range. This remains an issue with the current analysis, although having housing ownership enter separately did not change the results significantly.

Table 3.8. Count indices compared to individual indices

	PCA		PFA		MCA	
Formulation 1	Count	Individ.	Count	Individ.	Count	Individ.
Log Wealth	0.36	0.34	0.36	0.34	0.36	0.35
Log Income	0.32	0.33	0.33	0.33	0.33	0.33
Log Consumption	0.50	0.50	0.51	0.51	0.52	0.51
Formulation 2						
Log Wealth	0.48	0.42	0.48	0.40	0.49	0.43
Log Income	0.38	0.38	0.38	0.38	0.38	0.39
Log Consumption	0.55	0.57	0.57	0.56	0.57	0.58
Formulation 3						
Log Wealth	0.38	0.36	0.39	0.36	0.40	0.37
Log Income	0.34	0.34	0.35	0.34	0.35	0.34
Log Consumption	0.51	0.51	0.53	0.52	0.53	0.53
Formulation 4						
Log Wealth	0.45	0.39	0.46	0.35	0.44	0.39
Log Income	0.37	0.37	0.37	0.36	0.37	0.38
Log Consumption	0.55	0.56	0.56	0.55	0.56	0.56

Formulation 1: Counts of housing quality, water quality, appliances, health quality, social services. Formulation 2: As 1, but also with an asset count, plus number of rooms and home ownership and electricity indicators. 3: As 2, but also without an asset count. 4: As 2, but also without number of rooms and electricity indicators.

Having seen that asset indices correlate reasonably well with monetary measures of consumption, and sometimes wealth, we now examine how useful it is to use these indices in analytical research.

3.5. Estimating the Potential Bias in Research of Using Asset Indices

Researchers use asset indices in place of actual wealth as an explanatory variable in research. If they are to approximate, say, wealth well, we should see a similar level of variation explained, a similar magnitude and significance of coefficient on the proxy as on wealth, and little change in the covariates' coefficients (such as income). Furthermore, not including any wealth variable will indicate the extent of bias on the income coefficient if no wealth proxy is used.

Table 3.9 present the results of probit regressions of children's educational attainment (child currently enrolled if aged 6-14) on wealth, a wealth proxy, or no wealth indicator, income and a set of controls. The first column is the baseline regression using actual wealth. Of children aged 6-14 years we see that younger ones living in wealthier and urban households with more educated heads are more likely to be currently in school. Subsequent columns substitute this chapter's best proxy for wealth, the Asset Only index. In all cases, the coefficient on wealth remains significant albeit higher than baseline. The increase varies with the underlying index formulation and weighting methodology, from twice to six times higher, suggesting the household index is not only proxying wealth, but is also capturing the effects of other omitted variables; a slightly increased pseudo-R^2 supports this. The coefficient on age is similar in magnitude and significance to the baseline. Head-of-household education is still very significant but of a smaller magnitude. The most notable difference is that the urban dummy is no longer significant. Finally, compare the results of the final column, which omits wealth altogether. Log income now mimics the omitted wealth variable, with the coefficient becoming significant and of a similar magnitude. However, omitting a wealth proxy altogether makes the coefficient on income significant when it was not in the baseline. The choice of weighting is also important. PCA proxies are closest to the baseline results, with the main concern being the loss of significance on the urban dummy.

Table 3.9. Predicting child educational attainment

	1	2	3	4	5	6
Wealth Proxy	0.0020***	0.0044***	0.0090***	0.0077***	0.0090***	
	0.0006	*0.0009*	*0.0017*	*0.0015*	*0.0017*	
Log Income	0.0007	0.0001	0.0001	0.0001	0.0001	0.0018**
	0.0009	*0.0008*	*0.0008*	*0.0008*	*0.0008*	*0.0008*
Male	-0.0005	-0.0003	-0.0002	-0.0002	-0.0002	-0.0006
	0.0018	*0.0017*	*0.0017*	*0.0017*	*0.0017*	*0.0019*
Age	-0.0097***	-0.0091***	-0.0090***	-0.0091***	-0.0090***	-0.0100***
	0.0010	*0.0010*	*0.0010*	*0.0010*	*0.0010*	*0.0010*
Urban	0.0051**	0.0029	0.0027	0.0029	0.0027	0.0051**
	0.0025	*0.0023*	*0.0023*	*0.0023*	*0.0023*	*0.0026*
HoH Sex	0.0029	0.0027	0.0026	0.0027	0.0026	0.0021
	0.0033	*0.0030*	*0.0030*	*0.0030*	*0.0030*	*0.0032*
HoH Age	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
	0.0001	*0.0001*	*0.0001*	*0.0001*	*0.0001*	*0.0001*
HoH Educ	0.0018***	0.0013***	0.0013***	0.0013***	0.0013***	0.0020***
	0.0003	*0.0003*	*0.0003*	*0.0003*	*0.0003*	*0.0003*
District FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,085	6,096	6,096	6,098	6,096	6,085
Pseudo R^2	0.2854	0.2971	0.2982	0.2976	0.2982	0.2854

As a wealth measure, 1 uses log of wealth; 2-5 use the Asset Only index formulation with PCA, PFA, MCA or DiHOPIT weights; 6 excludes any wealth measure. HoH Sex, Age and Educ are head of household sex age and years of education. Coefficients reported are marginal effects, calculated at the multivariate average.

Thus, the use of an asset index as a wealth proxy is not unreasonable. The coefficient on the wealth proxy is likely to overestimate effects relative to actual wealth, but other coefficients remain largely unaffected. Including such a proxy, while not perfect, is an improvement on omitting wealth altogether, which can lead to a highly overestimated income coefficient or incorrect significance.

3.6. Conclusions

It is important to recognize the conceptual differences in aspects of economic well-being. I have noted two important components, living standards and economic security, as well as their relationship to the common monetary measures of consumption (closely related to living standards), wealth (a determinant of economic security) and income (directly related to both consumption and wealth and thus indirectly to living standards and economic security). The extent to which asset indices as presently constructed in the literature proxy for these various determinants of economic well-being has been examined, and potential multi-dimensional measures introduced. The key empirical findings are summarized below and combined with the conclusions from the methodological section to outline two sets of recommendations. The first regards approaches to index construction, given a researcher or policy maker's particular objectives; the second suggests considerations for those designing future household surveys.

3.6.1 Summary of key empirical results

Four main weighting strategies and a range of formulations of underlying variables found in the literature were examined. Measurement issues were addressed, such as discrimination amongst the wealthy, the number of variables to use, and the use of count variables. The potential bias researchers introduce through using or omitting such indices was also quantified. The key empirical findings are these:

1. The weighting methodologies examined, PCA, PFA, MCA, and to a lesser extent DiHOPIT, all weight indicator variables in a similar manner, and indices constructed from each method all correlate highly with each other. The choice of underlying variables is more important.

2. Asset indices using existing approaches generally approximate consumption more strongly than income or wealth, making them a better indicator of living standards than, say, economic security or status. This holds across weighting approaches and most formulations of underlying variables. However, a judicious choice of variables – asset ownership indicators which we would expect to be better wealth predictors than other household variables – produces a good wealth measure.

3. Many indices do a poor job distinguishing amongst the wealthy. The inclusion of 'wealthy' variables can improve discrimination between households in the upper half of the wealth distribution.

4. A number of categorically-related household variables can be counted as an aggregate variable. When a count of assets owned is used, the resulting index exhibits stronger correlations with household wealth.

5. Finally, I evaluate the potential bias in research if wealth proxies are used instead of actual wealth, and if no wealth proxy is used at all. Using self-reported wealth as a baseline, I find that the coefficient on wealth indices is consistently biased upwards. However, there is less bias across the specification compared to excluding a wealth measure altogether; exclusion of any wealth variable can lead to the coefficient on income being mistakenly significant or extremely overestimated.

3.6.2 Recommendations for constructing an asset index

Researchers and policy makers constructing an index need to consider three questions. Which weighting methodology should the use? Which underlying variables should they include in the construction? And do they need a one-dimensional or multidimensional measure?

With respect to weights, for researchers interested only in a single economic measure, whether wealth-specific or a general consumption / living standards measure, then all else being equal, there is a preference for PCA. It is easier and less computationally intensive to implement than DiHOPIT, is perhaps the most widely known approach, generally performs as well or better than PFA or MCA, and does not assume an underlying model. Following Kolenikov and Angeles (2009), I suggest ordinal variables entering PCA directly. However, for certain research objectives PCA is not the most appropriate. When we wish to compare index scores across periods or populations (such as countries or regions) then a DiHOPIT index is the most robust solution to cross-sample comparison. Researchers may also consider pooled PCA (pooling samples before running PCA to determine scoring coefficients and constructing an index), although this is inferior to DiHOPIT for this purpose. However, the use of count variables may well improve pooled PCA for cross-survey comparison. If statistical inference based on the estimation of weights is important, such as when we are testing whether scoring coefficients are stable across subsets of the sample (such as across the wealth distribution), then MCA is preferred, since it is designed for dichotomous and categorical variables and does not make the (incorrect) assumption of multivariate normality that PCA and PFA do.[107] If a model describing the relationship of the underlying variables to economic well-being is being used, then PFA or an explicit DiHOPIT model may be more appropriate than PCA or MCA, which are exploratory in nature. If there is no underlying model, then PFA is not recommended.

I next consider choosing underlying variables to include in constructing a single dimensional index. For consumption (or living standards), asset indicators mixed with housing and other non-asset characteristics is appropriate. If the effects of head-of-household covariates are independently important to the researcher, these should be excluded from the index construction; if not they may be included. Generally, the following variables appear to be relevant to general living standards or consumption in the Indonesian context: electricity, quality of roofing, wall and floor materials, nature of toilet, nature of drinking water, other housing quality indicators (such as separate kitchen and sleeping areas), number of rooms, ownership of various assets (appliances, vehicles, other assets such as savings, jewelry and livestock).[108] For wealth, excluding household covariates, using all strict asset-ownership indicators and number of rooms appears to perform well as a wealth index, although sensitivity analysis in other countries is needed. For income, even inclusion of head of household covariates, such as education and employment status, does not produce a strong income indicator. It is very difficult to construct an

[107] Note, I do not mean this consideration to apply if an household index is merely being used as an independent variable in a regression. This does not rely upon the precision with which scoring coefficients or weights were estimated.
[108] As wealth is a determinant of consumption, there is no need to exclude wealth indicators if a separate wealth index is not being constructed.

income-specific index from the variables we have encountered to date. This may be possible with future datasets if income-specific indicators are identified and collected, in which case an income-specific index could be constructed similarly to the wealth-specific index without covariates.

In addition, when targeting a particular distributional subset, it is important to include variables which discriminate amongst the target population. For example, while having electricity may separate households amongst the poor, it is unlikely to do so amongst the wealthy. Similarly, a broadband connection will discriminate amongst the wealthy but not the poor. Generally, the variables traditionally collected in developing country surveys do well at discriminating amongst the poor, but poorly amongst the upper half of the economic distribution. Researchers designing their own survey should consider carefully the populations they are trying to measure and which variables are appropriate to collect. Clearly, this requires a good working knowledge of the cultural and economic context in which they are working.

How many variables should be used when constructing an index? Ferguson *et al.* (2003) found that twenty four variables could be reduced to twelve without a significant drop in performance. I find similar results, suggesting that over twenty variables appears redundant (the *All* formulation did not perform more strongly than a well-considered formulation of less variables).

Finally, if a researcher is interested in multiple components of economic well-being, such as living standards and wealth separately, then some of the multidimensional extensions examined in this chapter may be promising. In particular, constructing separate wealth and consumption indices appears quite feasible given a judicious choice of variables in constructing each. This approach could be implemented with existing datasets, although it may be improved with refined survey designs. A multiple-component retention approach, whereby two or three components are kept from the PCA process and rotated, requires more development but may offer incremental improvements.

3.6.3 Recommendations for collection of future data

Much of this chapter concerns what can be done within the constraints of existing household survey data. Here I sketch considerations for future survey design, which draw both from the results of the chapter in particular and intuition more generally. It is vital to note that all of these require detailed cultural and economic knowledge of the setting. Where possible, asset categories should disaggregated. For example, whereas the IFLS asks about ownership of 'vehicles', it would be more useful to ask separately about cars, bicycles, motorbikes, and so forth. Similarly 'appliances' would be better collected separately as radios, sewing machines, etc. Moreover, asset classes such as cash and securities can be more productively distinguished as cash, savings accounts, equities, bonds, options, retirement funds and so forth. In a related sense, indicators better discriminating amongst the upper half of the economic distribution could be included, such as, depending on cultural context, ownership of computers, broadband access, overseas assets, multiple car ownership and perhaps mobile phones. Furthermore, while it has been shown to be feasible to construct a wealth-related index capturing the aspect of economic security related to a household's ability to weather shocks, we may also want a separate measure of how likely these shocks are to occur to a household. This requires variables on income stability and source. Lastly, including separate income indicators would be of considerable value, although we recognize that this is a difficult task, depending to an even greater extent on localized cultural and economic knowledge. This may not be possible in some settings, but remains a challenge for future researchers and survey designers.

I conclude by noting areas for further research. Measures of inequality from the distribution of an asset index are an important area requiring further research, as is comparing indices across regions and periods (samples). Categorical count variables appear to increase index performance as a wealth measure, but there are answered questions on how they should be constructed; I have used a simple unweighted-sum, but various weights could be explored. Finally, further work on multiple component retention and rotation could improve the use of asset indices as measures of all aspects household economic well-being.

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Appendix One: Trade Variable Construction

This appendix outlines how each trade variable used in our second-stage regressions was constructed. The main trade variables are industry-specific real exchange rates, effective rates of protection, import penetration rates, and export shares of production.

INDUSTRY-SPECIFIC TRADE-WEIGHTED REAL EXCHANGE RATES

Adapting Goldberg (2004), we construct both export- and import-weighted real exchange rates for each industry *j*. Goldberg suggests, respectively:

$xer_t^j = \sum_c w_t^{jc} \times rer_t^c$, where $w_t^{jc} = \dfrac{X_t^{jc}}{\sum_c X_t^{jc}}$, and

$mer_t^j = \sum_c w_t^{jc} \times rer_t^c$, where $w_t^{jc} = \dfrac{M_t^{jc}}{\sum_c M_t^{jc}}$,

where rer_t^c are the bilateral real exchange rates with each Brazilian trading partner *c*.

Rather than deriving real exchange rates for every trading partner by industry and year, a large undertaking, we have ranked countries by decreasing size of imports (exports) in each industry, and included those countries who (i) make up the first 95 percent of imports (exports), and (ii) whose imports (exports) are over 1 percent of the total within that industry. To reduce spurious volatility in the exchange rate series due to a changing composition of the set of countries in the annual weights, we depart from Goldberg by defining our weighted exchange rates with constant weights across the period:

$$xer_t^j = \sum_c w_{8599}^{jc} \times rer_t^c \text{ , where } w_{8599}^{jc} = \frac{\sum_{t=1985}^{1999} X_t^{jc}}{\sum_c \sum_{t=1985}^{1999} X_t^{jc}} \text{ , and}$$

$$mer_t^j = \sum_c w_{8599}^{jc} \times rer_t^c \text{ , where } w_{8599}^{jc} = \frac{\sum_{t=1985}^{1999} M_t^{jc}}{\sum_c \sum_{t=1985}^{1999} M_t^{jc}} .$$

These weights are based on a country's share of trade over the period 1985-1999. All trading partners of significance over the period are included, and their real exchange rates are weighted identically in each year, so the variation in the aggregate industry exchange rate comes from changes in trading partners' exchange rates, rather than trade volume or inclusion/exclusion in different years.

We use trade data from COMTRADE at the SITC 4-digit level. A concordance was constructed to match each SITC2 4-digit industry code to the more aggregated industries of the ERP data from Kume *et al* (2000). Imports (exports) are then summed by country over these ERP industries to give us M_t^{jc} (X_t^{jc}). Bilateral real exchange rates were constructed by multiplying each country's nominal exchange rate (in local currency per Real) by the ratio of the Brazilian price index to the partner country price index, where the WPI (wholesale price index) was used where available, and the CPI (consumer price index) otherwise. Countries for which neither a full time series of WPI or CPI were available were excluded. For the nontradable sector, we constructed economy-wide real exchange rates, using imports and exports with trading partners across all industries to derive country weights.

EFFECTIVE RATES OF PROTECTION

ERPs from 1985-1999 are available from Kume *et al.* (2000). We have used them as reported in Abreu (2004). However, the industry classifications differ from those available in the PNAD. Adapting the concordance used by Pavcnik *et al.* (2004), we averaged ERPs across certain ERP industries using lagged industry imports as weights. The summary final concordance is reported in Table 1.2 in the main text.

IMPORT PENETRATION RATE AND EXPORT SHARE OF PRODUCTION

Both of these variables were constructed in the same way; the raw data for both is from Muendler (2003), (available at http://www.econ.ucsd.edu/muendler/html/brazil.html). These data are given by *Nível 80* (an official Brazilian classification), a different industry classification than that afforded us by the PNAD, so a concordance from *Nível 80* to *Nível 100* (also available on Muendler's website) was used to move to *Nível 100*, and a second concordance from *Nível 100* to the ERP industry categories was constructed by the authors to standardize industries. As with ERPs, import weights were then used to average certain industry import penetration and export share to arrive at data series for the final industries used in the chapter.

Table A1.1. Industry standardization: steps and concordances

Trade variable	Initial industry classification	Concordance steps	Concordances used
Trade-weighted RER	SITC2	SITC2 to ERP	SITC2 to ERP (authors)
		ERP to final (PNAD)	ERP to PNAD (authors)
ERP	Unknown (referred to here as ERP)	ERP to final (PNAD)	ERP to PNAD (authors)
Import penetration	Nivel 80	Nivel 80 to Nivel 100	Nivel 80 to Nivel 100 (Muendler)
		Nivel 100 to ERP	Nivel 100 to ERP (authors)
		ERP to final (PNAD)	ERP to PNAD (authors)
Export share	Nivel 80	Nivel 80 to Nivel 100	Nivel 80 to Nivel 100 (Muendler)
		Nivel 100 to ERP	Nivel 100 to ERP (authors)
		ERP to final (PNAD)	ERP to PNAD (authors)

CONCORDANCES

There are a number of concordances used to standardize industries across the various trade data. The final industry classifications were driven by those available in the PNAD. The concordances used were:

- ERP industry (i.e. the industry classification used by *Kume et al.* (2000), which is similar to *Nivel 50*) to our final industry classification (author constructed).
- ERP to PNAD (author constructed, based on Pavcnik *et al.* (2004)).
- *Nivel 80* to *Nivel 100* (available from Muendler).
- *Nivel 100* to ERP (author constructed).
- SITC2 to ERP (author constructed).

The steps taken to standardize each trade variable’s industry classifications are listed in Table 1.10.

Appendix Two: Supplementary Results to Chapter Two

Table A2.1. Robustness tests for impact on malnutrition

Panel A: Probability that Weight-for-age Z-score < -2SD (Wasting)

	LP Model	LP Model	LP Model	Probit*	Probit*	Probit*	Logit	Logit	Logit
Posyandu effect	-0.10**	-0.20***	-0.22***	-0.10**	-0.26***	-0.28***	-0.49**	-1.21***	-1.30***
	0.021	*0.002*	*0.004*	*0.015*	*0.000*	*0.001*	*0.015*	*0.001*	*0.001*
Posyandu * Urban			0.11			0.12			0.55
			0.252			*0.250*			*0.286*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Village	Village	Village	Village	Village	Village	Village	Village	Village
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	2,048	2,048	2,048	2,024	1,923	1,923	2,024	1,923	1,923

Notes: Standard errors clustered at village level. P-values report in italics. Posyandu effect: cohort dummy takes 1 if born from 2 years before posyandus until 3 years after posyandus, 0 if born 4-7 years before. Individual controls include child's age, sex, urban, whether fasting, whether child had in the last four weeks a headache, runny nose, cough, fever, stomach ache, nausea, vomiting or severe diarrhea, parents' education. Household controls include household income, wealth, food and non-food consumption. Time-varying village controls include whether at time of birth there was a sub-district community health center, solid waste and sewage disposal, public transport and piped drinking water. * Probit reports marginal effects.

Table A2.1. Robustness tests for impact on malnutrition (cont.)

Panel B: Probability that Height-for-age Z-score < -2SD (Stunting)

	LP Model	LP Model	LP Model	Probit*	Probit*	Probit*	Logit	Logit	Logit
Posyandu effect	-0.12***	-0.19***	-0.21***	-0.13***	-0.22***	-0.24***	-0.54***	-0.92***	-0.99***
	0.001	*0.002*	*0.002*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*
Posyandu * Urban			0.11			0.11			0.46
			0.149			*0.164*			*0.191*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Village	Village	Village	Village	Village	Village	Village	Village	Village
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	2,048	2,048	2,048	2,047	1,972	1,972	2,047	1,972	1,972

Notes: Standard errors clustered at village level. P-values report in italics. Posyandu effect: cohort dummy takes 1 if born from 2 years before posyandus until 3 years after posyandus, 0 if born 4-7 years before. Individual controls include child's age, sex, urban, whether fasting, whether child had in the last four weeks a headache, runny nose, cough, fever, stomach ache, nausea, vomiting or severe diarrhea, parents' education. Household controls include household income, wealth, food and non-food consumption. Time-varying village controls include whether at time of birth there was a sub-district community health center, solid waste and sewage disposal, public transport and piped drinking water. * Probit reports marginal effects.

Table A2.2. Robustness tests for impact on malnutrition

Panel A: Probability that Weight-for-age Z-score < -2SD (Wasting)

	Different Cohort Definitions						Falsification Experiment		
	1	2	3	4	5	6	7	8	9
Posyandu effect (cohort coefficient)	-0.20***	-0.15**	-0.18***	-0.19**	-0.14***	-0.06	-0.01	-0.00	0.01
	0.002	*0.036*	*0.001*	*0.016*	*0.005*	*0.148*	*0.514*	*0.772*	*0.413*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Village	Village	Village	Village	Village	Village	Village	Village	Village
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,048	2,462	2,962	2,328	2,204	3,059	4,727	6,824	4,773

Notes: All regressions are linear probability model. Standard errors clustered at village level. P-values report in italics. Posyandu effect: cohort dummy takes: (i) 0 if date of birth 4-7 years before first village posyandus, 1 if 2 years before to 3 years after; (ii) 0 if 3-8 years before, 1 if 1-5 years after; (iii) 0 if 4-9 years before, 1 if 2 years before to 5 years after; (iv) 0 if 4-9 years before, 1 if 1-5 years after; (v) 0 if 3-7 years before, 1 if 2 years before to 3 years after; (vi) 0 if 2-7 years before, 1 if 1 year before to 4 years after; (vii) 0 if 1-5 years after, 1 if 6-10 years after; (viii) 0 if 2 years before to 5 years after, 1 if 6-13 years after; (ix) 0 if 2 years before to 3 years after, 1 if 4-9 years after. Individual controls include child's age, sex, urban, whether fasting, whether child had in the last four weeks a headache, runny nose, cough, fever, stomach ache, nausea, vomiting or severe diarrhea, parents' education. Household controls include household income, wealth, food and non-food consumption. Time-varying village controls include whether at time of birth there was a sub-district community health center, solid waste and sewage disposal, public transport and piped drinking water. * Probit reports marginal effects.

Table A2.2. Robustness tests for impact on malnutrition (cont.)

Panel B: Probability that Height-for-age Z-score < -2SD (Stunting)

	Different Cohort Definitions						Falsification Experiment		
	1	2	3	4	5	6	7	8	9
Posyandu effect (cohort coefficient)	- 0.19***	- 0.16**	-0.13**	-0.15*	-0.16***	-0.00	-0.03*	-0.03*	-0.02
	0.002	*0.021*	*0.017*	*0.086*	*0.002*	*0.939*	*0.083*	*0.054*	*0.186*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Village	Village	Village	Village	Village	Village	Village	Village	Village
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,048	2,462	2,962	2,328	2,204	3,059	4,727	6,824	4,773

Notes: All regressions are linear probability model. Standard errors clustered at village level. P-values report in italics. Posyandu effect: cohort dummy takes: (i) 0 if date of birth 4-7 years before first village posyandus, 1 if 2 years before to 3 years after; (ii) 0 if 3-8 years before, 1 if 1-5 years after; (iii) 0 if 4-9 years before, 1 if 2 years before to 5 years after; (iv) 0 if 4-9 years before, 1 if 1-5 years after; (v) 0 if 3-7 years before, 1 if 2 years before to 3 years after; (vi) 0 if 2-7 years before, 1 if 1 year before to 4 years after; (vii) 0 if 1-5 years after, 1 if 6-10 years after; (viii) 0 if 2 years before to 5 years after, 1 if 6-13 years after; (ix) 0 if 2 years before to 3 years after, 1 if 4-9 years after. Individual controls include child's age, sex, urban, whether fasting, whether child had in the last four weeks a headache, runny nose, cough, fever, stomach ache, nausea, vomiting or severe diarrhea, parents' education. Household controls include household income, wealth, food and non-food consumption. Time-varying village controls include whether at time of birth there was a sub-district community health center, solid waste and sewage disposal, public transport and piped drinking water. * Probit reports marginal effects.

Table A2.3. Robustness tests - different balanced panels

Panel A: Probability that Weight-for-age Z-score < -2SD (Wasting)

		Balanced Panels, Min:				
	Unbalanced	1	2	3	4	5
Posyandu effect (cohort coefficient)	-0.20***	-0.26***	-0.27***	-0.27***	-0.25***	-0.28***
	0.002	*0.001*	*0.001*	*0.001*	*0.004*	*0.004*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Village	Village	Village	Village	Village	Village
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,048	1,090	991	977	840	778

Notes: All regressions are linear probability model. Standard errors clustered at village level. P-values report in italics. Posyandu effect: cohort dummy takes: (i) 0 if date of birth 4-7 years before first village posyandus, 1 if 2 years before to 3 years after; (ii) 0 if 3-8 years before, 1 if 1-5 years after; (iii) 0 if 4-9 years before, 1 if 2 years before to 5 years after; (iv) 0 if 4-9 years before, 1 if 1-5 years after; (v) 0 if 3-7 years before, 1 if 2 years before to 3 years after. Individual controls include child's age, sex, urban, whether fasting, whether child had in the last four weeks a headache, runny nose, cough, fever, stomach ache, nausea, vomiting or severe diarrhea, parents' education. Household controls include household income, wealth, food and non-food consumption. Time-varying village controls include whether at time of birth there was a sub-district community health center, solid waste and sewage disposal, public transport and piped drinking water. * Probit reports marginal effects.

Table A2.3. Robustness tests - different balanced panels (cont.)

Panel B: Probability that Height-for-age Z-score < -2SD (Stunting)

		Balanced Panels, Min:				
	Unbalanced	1	2	3	4	5
Posyandu effect (cohort coefficient)	-0.19***	-0.13*	-0.14*	-0.14*	-0.17**	-0.19**
	0.002	*0.068*	*0.062*	*0.063*	*0.033*	*0.030*
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Village	Village	Village	Village	Village	Village
Year of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying village controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,048	1,090	991	977	840	778

Notes: All regressions are linear probability model. Standard errors clustered at village level. P-values report in italics. Posyandu effect: cohort dummy takes: (i) 0 if date of birth 4-7 years before first village posyandus, 1 if 2 years before to 3 years after; (ii) 0 if 3-8 years before, 1 if 1-5 years after; (iii) 0 if 4-9 years before, 1 if 2 years before to 5 years after; (iv) 0 if 4-9 years before, 1 if 1-5 years after; (v) 0 if 3-7 years before, 1 if 2 years before to 3 years after. Individual controls include child's age, sex, urban, whether fasting, whether child had in the last four weeks a headache, runny nose, cough, fever, stomach ache, nausea, vomiting or severe diarrhea, parents' education. Household controls include household income, wealth, food and non-food consumption. Time-varying village controls include whether at time of birth there was a sub-district community health center, solid waste and sewage disposal, public transport and piped drinking water. * Probit reports marginal effects.

Fig. A2.1. Posyandu effect on underweight by relative age

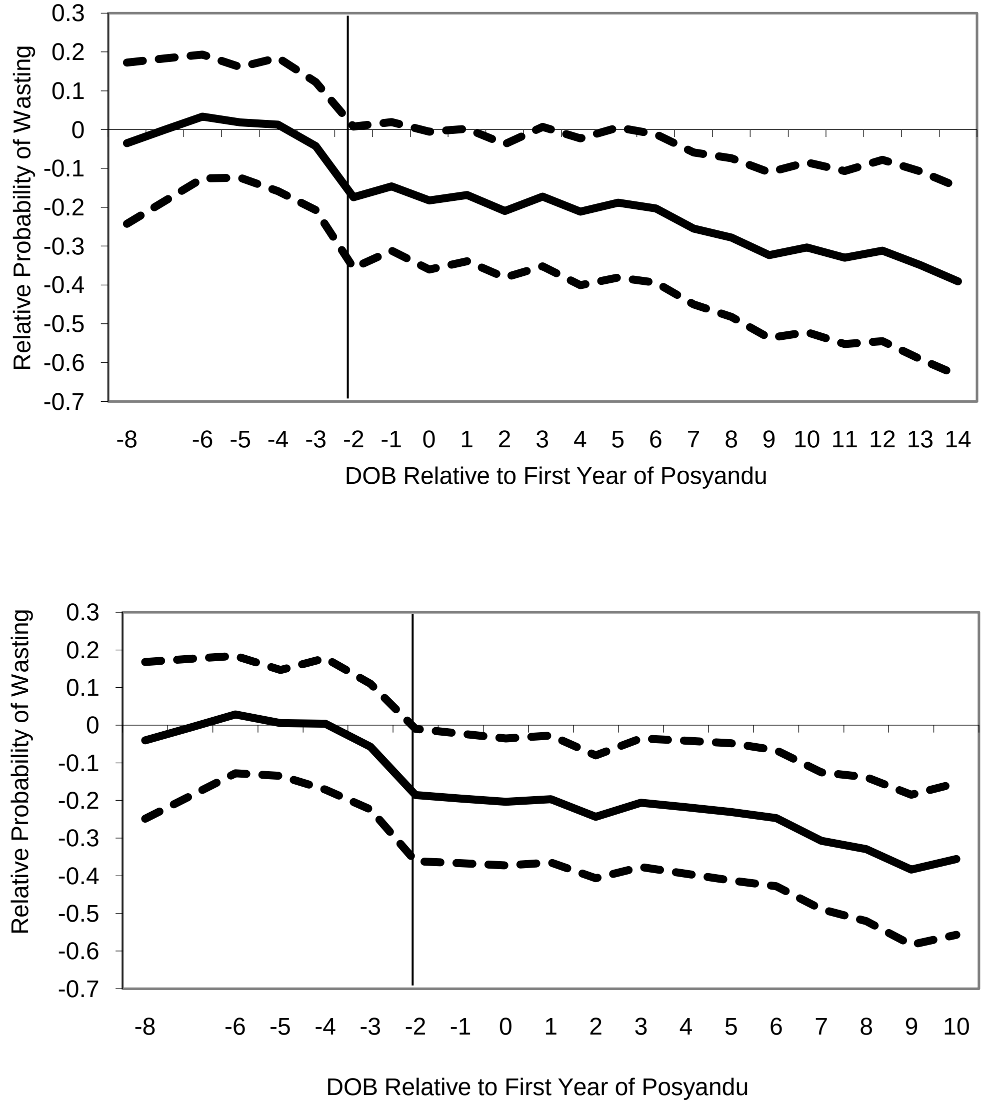
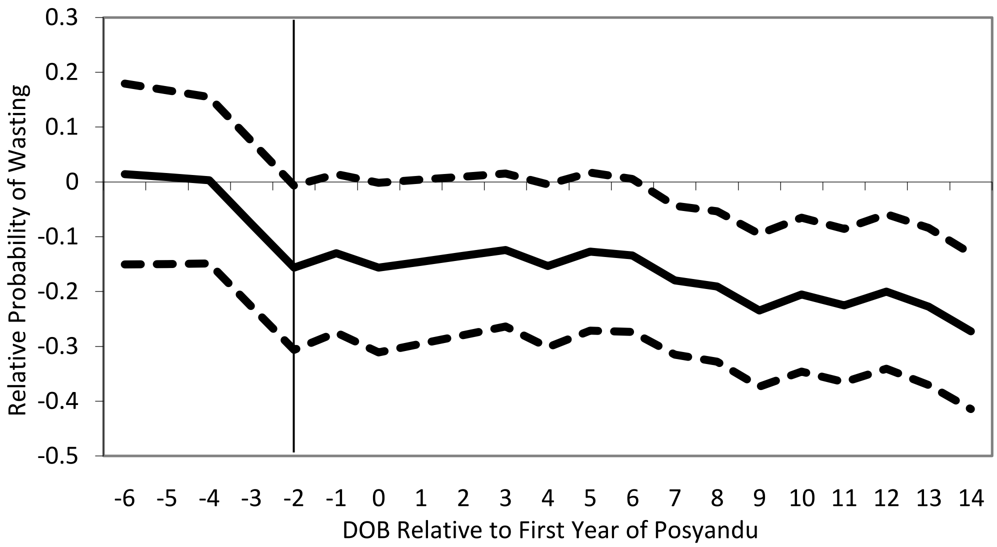


Fig. A2.1. Posyandu effect on underweight by relative age (cont.)



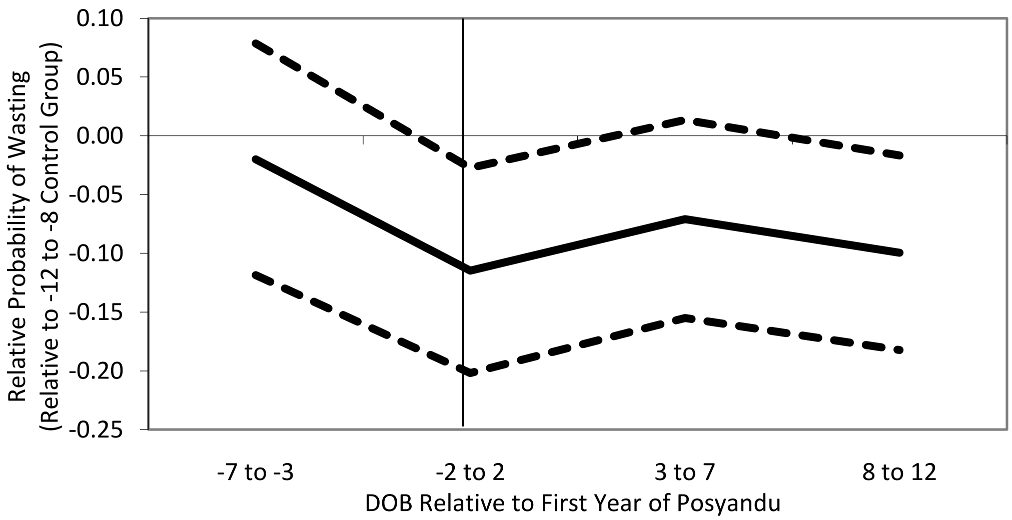
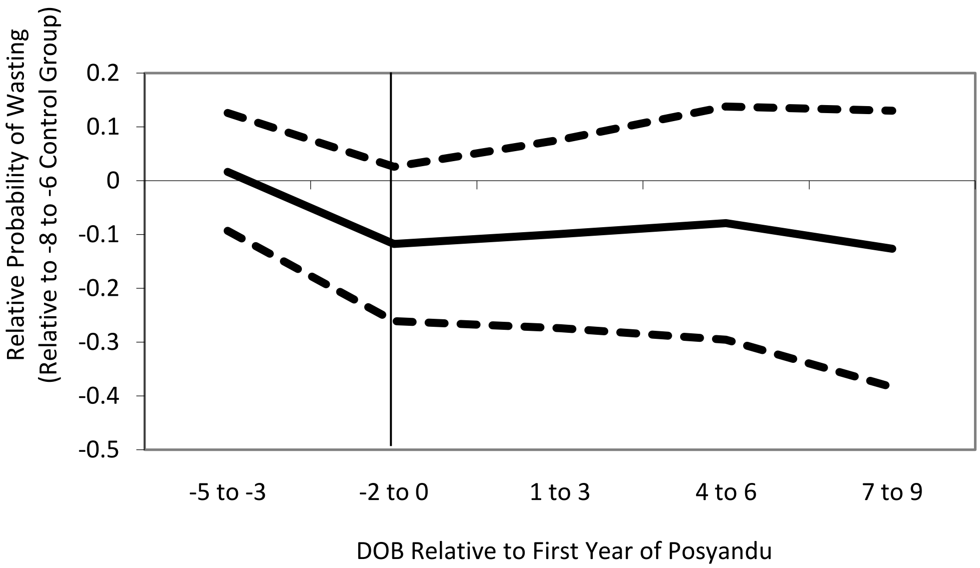


Fig. A2.1. Posyandu effect on underweight by relative age (cont.)



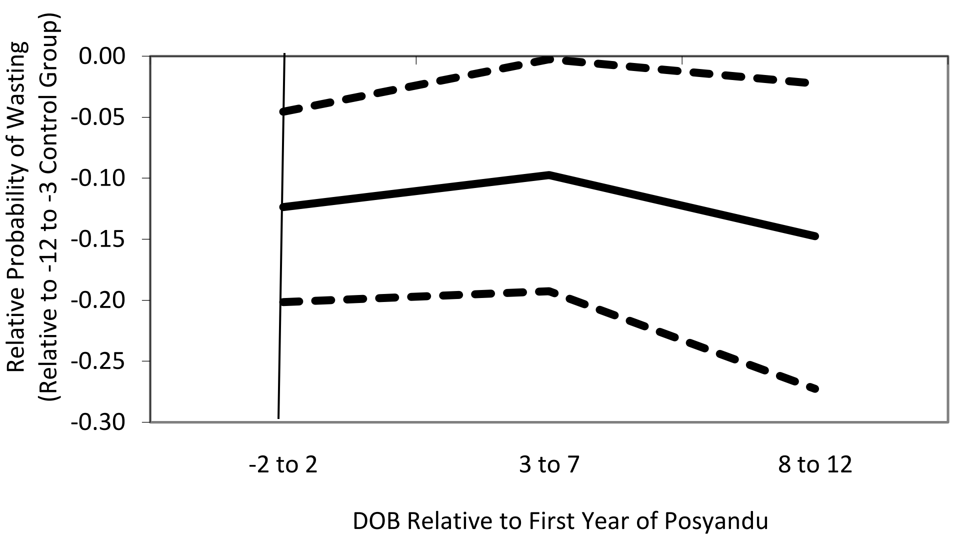
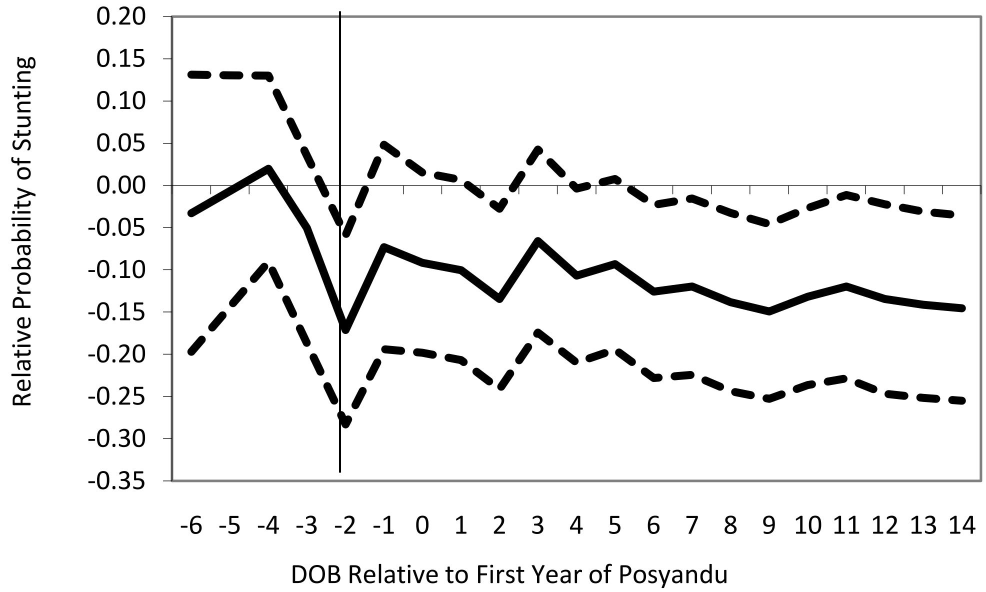


Fig. A2.2. Posyandu effect on stunting by relative age



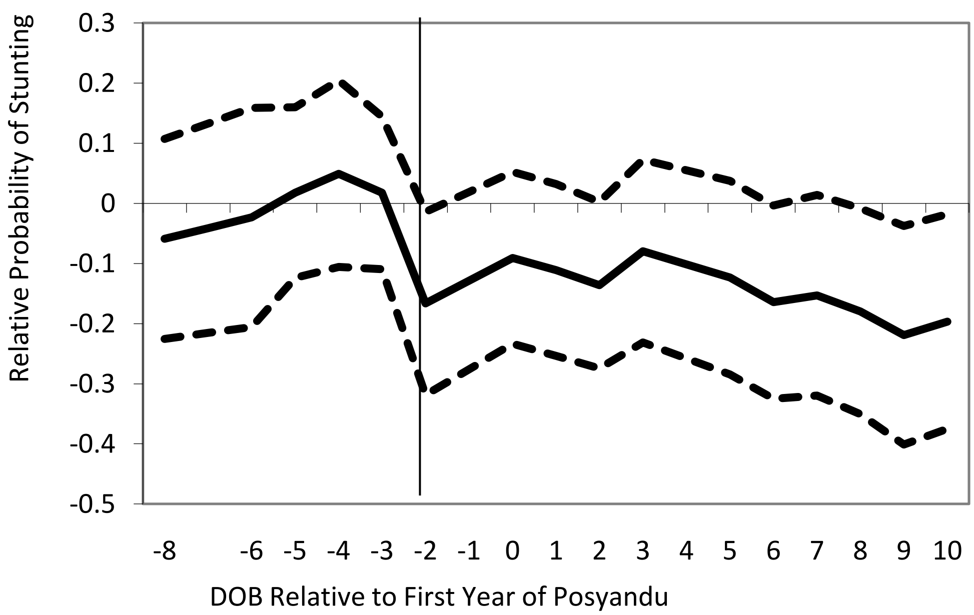
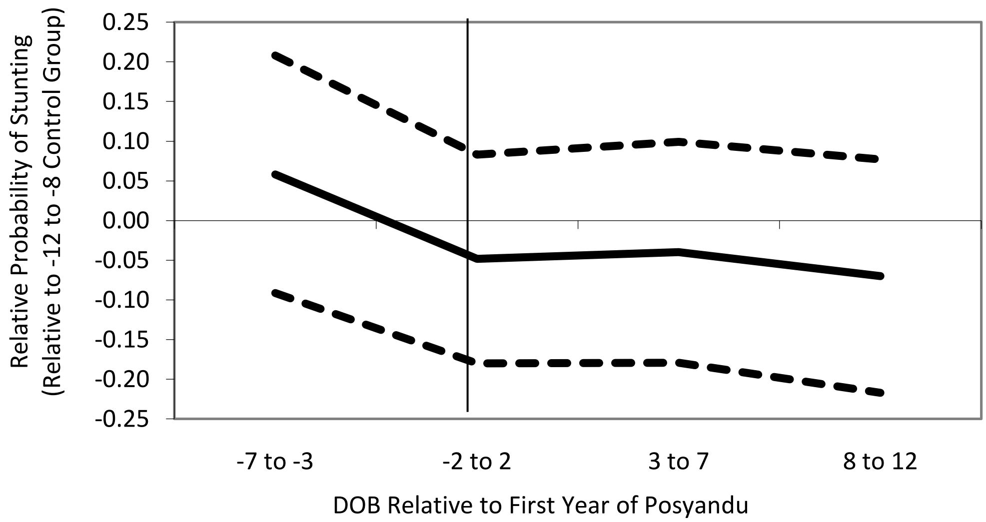
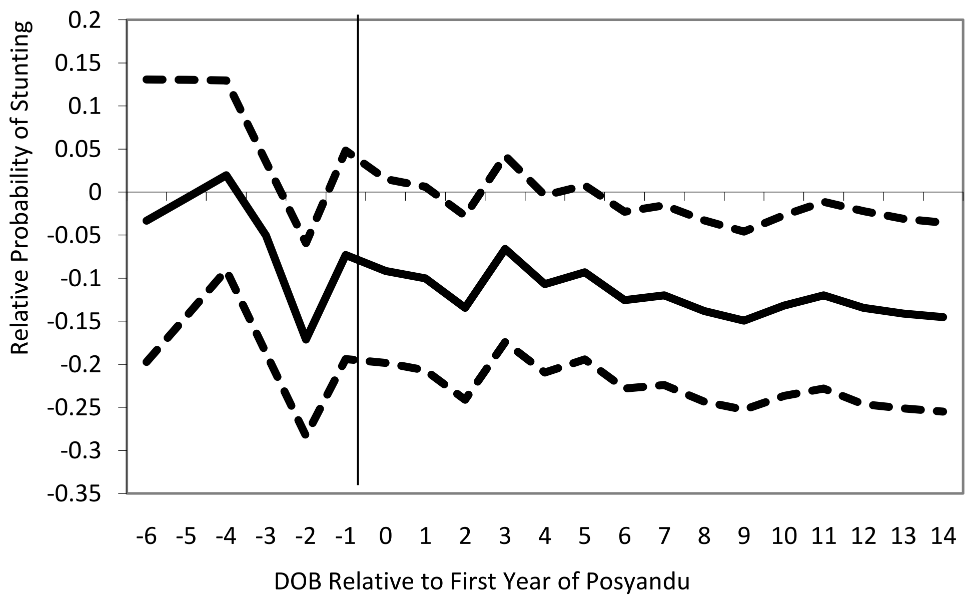


Fig. A2.2. Posyandu effect on stunting by relative age (cont.)





Appendix Three: Constructing Household Income, Wealth and Consumption

The IFLS asked many detailed questions on household expenditures, individual and household income, and individual and household assets. The following describes the different variables used to construct the household income, wealth and consumption measures used in this paper.

Income

Household income was constructed by summing all individual income, made up of both non-labor income and labor market income, and adding it to household income from farm and non-farm businesses (discussed under wealth). The survey asked about eight sources of non-labor income: retirement, scholarship, insurance money, winnings/lottery, Arisan,[109], transfers, earnings, and other. Labor market income was derived as follows:

Private or Government worker (i.e. salaried): the value of remuneration including benefits was asked for both the last month and the last year. The larger of the remuneration over the last year and over the last month when annualized was taken as the annual labor market income, on the assumption that last month's probably

[109] A kind of group lottery, conducted at periodic meetings. Each member contributes a set amount of money, and the pool is given to the tenured member whose name is drawn at random.

represents the current level of salary given possible increases over the last year, but that an unrepresentatively low last month's salary can be ignored in favor of last year's total labor income.

Self-employed workers: income from self-employment labor was asked both for last month and over the last year. In this case, last year's income (when available) was preferred to annualizing last month's income, as self-employed income is likely more volatile than for salaried workers; income reported over an annual period better smoothes these fluctuations. Income from last month was annualized where last year's income was unavailable.

Respondents were asked about both their primary and secondary jobs. These could be a mixture of salaried and self-employment, and the relevant income construction method outlined above was used to calculate income for each, and then primary and secondary labor market incomes aggregated to give total labor market income.

Two different household income variables were constructed. The first included business income if it was negative; the second variable excluded negative business income. This applies to only 938 of 10,079 households with income data. Of this 938, the average difference between the two income variables was IDR 9m, or about USD 1,000; only 208 households had a difference in income definitions greater than IDR 1m, and only 71 a difference greater than IDR 10m. Results throughout the paper remain the same using either variable; the variable excluding negative business income is presented throughout.

Household Assets (Wealth)

The survey asked about assets in three parts: non-business household assets, farm business assets and non-farm business assets. Non-business assets asked about any of the following owned by the respondent[110] or any member of the household: house occupied, other house or building, non-agricultural land, livestock/poultry/fishpond, vehicles (cars, boats, bicycles, motorbikes), household appliances (radio, tape recorder, TV, fridge, sewing machine, computer), savings or certificates, receivables, jewelry, household furniture and utensils, and other. For each category, the total asset value and annual income derived was asked, as well as the percentage owned by the household. Asset values for each category, adjusted for partial ownership, were aggregated to give total household non-business wealth. Annual income derived from each category, adjusted for partial ownership, was aggregated to give household income from non-business assets (used in calculating total household income, described above).

Similarly, if a household owned, or partially-owned, a farm business, respondents were asked about the total asset values, annual income derived, and percentage owned by household members, for the following categories: farm land, hard stem plants (coconut,

[110] One respondent per household answered this section of the survey.

coffee, cloves, rubber, etc), house or building used for the farm business, livestock/poultry/fish pond, vehicles (bicycles, motor bikes, car/truck, and water vehicles), tractor, heavy equipment (like farming machines, generator, etc), small tools (like saws, axes, machetes, forks, plows, hoes, etc), and other assets. Again, the household's share of asset value and income derived was aggregated across categories, to give total household farm business wealth, and household income from the farm business.

Finally, the process was repeated for non-farm businesses, using the categories: land, building, four-wheeled motor vehicles, other vehicles, and non-farm equipment. Total business income, including production for self-consumption, was also asked.

Consumption

Households were asked about food and non-food consumption. Expenditure over the last month was asked for: utilities (electricity, water, fuel, telephone and the like), personal toiletries, household items (such as cleaning supplies), domestic services and servants' wages, recreation and entertainment, transportation, sweepstakes and lotteries, *Arisan*, and non-food items given regularly to non-household parties. The value of these items self-produced for household consumption over the last month was also asked.

Expenditure for the last year was asked for: clothing for children and adults, household supplies and furniture (such as bedding), medical costs, ritual ceremonies and gifts (such as weddings, charity, tithe), taxes (including property, vehicle, income, sales taxes), other (such as televisions, cars, livestock, house), and the value of any of these given to parties outside the house on an irregular basis. Schooling expenses over the last year by tuition and fees, uniforms and supplies, transportation and lunches, and boarding/rent for children outside the household were collected. Annualizing the monthly consumption items and adding them to the annual consumption items and schooling gives the household's total annual non-food consumption.

Food consumption during the last week, broken down by expenditure and self-produced or received, covering a very detailed list of categories, was annualized and aggregated to give household food consumption; total household consumption is then the sum of total food and non-food consumption.